Portfolio Optimization using Bayesian Networks and BiLSTM Neural Network Model

*An integrated approach combining probabilistic modeling and deep learning for smarter investment strategies.

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***Abstract*—This research proposes a novel hybrid portfolio optimization model by integrating Bayesian Networks and BiLSTM neural networks. From three base studies of stock price prediction, probabilistic modeling, and risk-based portfolio optimization, our model leverages the time feature extraction ability of BiLSTM and probabilistic inference capability of Bayesian Networks. The BiLSTM model outputs stock price predictions, while Bayesian Networks accept historical and external market variables' correlation scores to scrutinize the stability and risk level of a stock. The two-tier system enhances the short-run prediction accuracy as well as the portfolio selection efficacy based on the risk tolerance level of an investor. Pilot findings show highly promising prediction rates of nearly 70 percent and suggest promise in real-world practice applications in finance decision-making.**

***Index Terms*—Portfolio Optimization, Bayesian Networks, BiLSTM, Stock Market Prediction, Time Series Forecasting, Risk Assessment, Deep Learning, Financial Modeling, Probabilistic Inference.**

I. Introduction

Financial markets are very closely knit, highly volatile, and possess interdependent variables, making prediction and decision-making a tough challenge. Investors are always on the lookout for models that allow them to make portfolio choices founded on anticipated returns and associated risks. Traditional quantitative models such as the Capital Asset Pricing Model (CAPM), Efficient Market Hypothesis (EMH), and Mean-Variance Optimization (MVO) have long been foundation models in portfolio management and financial forecasting. These models, however, have a tendency to make assumptions—such as normality of returns, linearity of relationships, and time-invariant market conditions—that might not always be true in reality. This leads to poorer performance, particularly in highly dynamic and non-linear systems like stock markets.

Besides, these conventional approaches are likely to falter in uncovering the intricate inter-dependent relationships between macroeconomic variables, firm-specific information, investor sentiment, and historical trends. They are not flexible in reflecting real-time adjustments and do not accommodate uncertainty and missing data, both of which dominate financial settings. For because as global news, events, and changing economic signals have more impact in the creation of markets, models that can keep up with such complexity are increasingly significant.

In an attempt to cover this gap, advancements in artificial intelligence (AI) have presented financial modeling, forecasting, and decision support systems with new opportunities. Deep learning architectures such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) and Bidirectional LSTM networks have been promising a lot in the context of time series forecasting. CNNs can learn local or spatial features from data, while LSTMs can learn long-term temporal dependencies and therefore they are a good combination to predict financial time series.

However, as powerful as deep learning models are, they function largely as "black boxes." They might not be very interpretable and lack the ability to incorporate uncertainty or expert judgment into the decision-making process. That is where probabilistic graphical models such as Bayesian Networks (BNs) come in. BNs provide a structured and interpretable means of specifying dependencies between variables in the form of directed acyclic graphs (DAGs). They are particularly valuable in expressing uncertain relations and both quantitative evidence and qualitative opinion. Bayesian Networks can be applied in financial markets to estimate conditional probabilities of outcomes like direction of the market or stock stability given some evidence like economic indicators or measures of firm performance.

In this research paper, we propose a hybrid portfolio optimization approach through the integration of BiLSTM model and Bayesian Networks. We intend to benefit from the prediction capability of deep learning along with probabilistic inference and interpretability that come with Bayesian models. We begin by using a BiLSTM model to predict the next day's change in price of a single stock. The prediction is not utilized individually. Rather, it is used to input into a Bayesian Network with other extraneous variables—historical volatility, volumes of trades, performance by sector, and macro indicators—to determine each stock's level of stability and

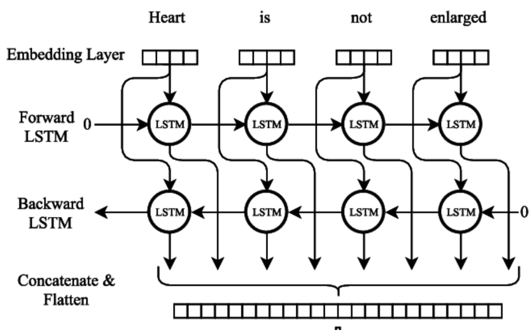

Fig. 1. BiLSTM Architecture

risk. Having the two levels permits us to look beyond naked forecasts and be informed in choosing composition of portfolio from both foretold returns as well as derived risk profiles.

Our work is inspired by three main research papers: one on predicting stock prices using BiLSTM model, one on predicting stock index direction using Bayesian Networks, and one on portfolio optimization using Value at Risk (VaR) and investor-specific risk attitudes. Fusing these concepts with modifications, we aim to create a stable, scalable, and interpretable system that can aid individual and institutional investors in maximizing their portfolios depending on varying market scenarios. Moreover, we utilize real-time financial data from reliable APIs such as Alpha Vantage, Yahoo Finance, and Google Finance. These provide access to high-frequency historical prices, sectoral indices, and technical indicators, making our model dynamic and sensitive to current market trends. Unlike most models that rely on historical prices alone, our model utilizes both historical and external inputs, reflecting the multidimensional nature of modern financial markets.

The rest of the paper is arranged as follows: Section 2 is a systematic literature review of previous work and methodologies. Section 3 elaborates the Contribution, including data preprocessing, architecture of BiLSTM model, construction of a Bayesian Network, and risk analysis. Section 4 highlights the Novelty in our research and covers the implementation and experiment settings. Section 5 analyzes the model's performance based on metrics such as prediction accuracy and volatility of a portfolio. Finally, Section 6 summarizes the paper with important findings, limitations, and future work.

With the incorporation of deep learning and probabilistic reasoning, this paper contributes a complete and intelligent portfolio optimization methodology better aligned with the realities of the modern financial world.

II. Literature Review

Stock market forecasting and portfolio optimization are fundamental issues in finance studies because of the dynamic, volatile, and high-dimensional characteristics of financial markets. Financial variables are influenced by extremely wide range of factors, from sector performance and macroeconomic indicators to investor sentiment and exogenous shocks, which renders prediction and decision-making inherently challenging. In response, researchers have explored alternative computational models and statistical frameworks to enhance forecast accuracy, better manage risk, and guide investors in decision-making. Geometric Brownian Motion (GBM), Bayesian Networks (BNs), and deep learning architectures such as CNN-LSTM have been robust frameworks to model and analyze behavior in markets.

Shahidin et al. (2021) present a robust portfolio optimization technique with much emphasis being put on the individual investor's own risk appetite. They apply Geometric Brownian Motion to approximate stochastic stock price dynamics and Value at Risk (VaR) estimates to quantify potential losses under adverse situations. This two-stage technique enables the investor to design portfolios according to their own risk appetites, either risk-averse or risk-seeking, yet still take into account historical volatility. What makes their work stand out is its relevance: rather than describing a typical theoretical framework, they develop an asset allocation system that can be applied immediately in real-world investment environments, and both private investors and asset managers gain practical usability from it. [3]

Separately, Malagrino et al. (2018) utilize Bayesian Networks to address the issue of stock market daily direction prediction, focusing on Brazil's iBOVESPA index. Their model combines local and international market indicators to create a 24-hour predictive time horizon that echoes the fast-paced, interconnected nature of modern markets. By representing causal dependencies between economic variables through a Directed Acyclic Graph (DAG), Bayesian Networks yield an interpretable and flexible probabilistic model. One of the main features of their approach is the ability to dynamically revise predictions with arriving data, a trait particularly useful in volatile environments. Achieving as high as 78 percent accuracy in their prediction efforts, their work underscores the utility of BNs in capturing uncertainty and inter-variable dependencies in financial systems. [2]

On another track, Bagde (2023) investigates the potential of deep learning in financial forecasting by developing a hybrid model that combines Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) and BiLSTM models. CNNs are extremely capable of extracting spatial and structural features from data, whereas LSTMs are specifically designed to handle long-term dependencies and sequential information in time series. The fusion of the two architectures constitutes a robust hybrid model that has the ability to learn both local patterns and universal temporal patterns. Bagde's contribution is also singular in that it applies on live noisy financial data, testing the model robust and versatile. The CNN-LSTM model, besides offering high prediction accuracy, also adapts well to the dynamics of continuous price fluctuations under live trading scenarios. Although we did not use the CNN-LSTM framework in our implementation, this paper gave us an inspiration to research more about Bidirectional LSTM models and try them out in our implementation. [1]

Together, these three articles make complementing but competing contributions to decision support and financial modeling literature. Shahidin et al. affirm the importance of incorporating investor risk aversions into portfolio planning, Malagrino et al. offer a probabilistic rationale framework that is sensitive to economic interdependencies and uncertainty, and Bagde shows the efficacy of deep learning to identify faint, non-linear relationships in stock returns. Although each of them has its own merits, there is a clear void in integrating these methodologies into one system that addresses both prediction accuracy and intelligent risk assessment.

Motivated by this lack, our research presents a hybrid model that marries the predictive power of BiLSTM models with the explainability and probabilistic reasoning of Bayesian Networks. In so doing, we aim to build an inclusive framework that not only predicts stock price fluctuations with high accuracy but also evaluates the underlying risk and stability of each stock in line with market dynamics and extrinsic influences. This hybridization offers a more integrated view of portfolio optimization—one that allows for the multivariate nature of financial markets, combining machine-derived forecasts with human-like decision-making in the face of uncertainty. The outcome is a model designed to serve institutional and individual investors alike seeking actionable intelligence in an information-rich, fast-changing market environment.

III. Contribution

This section presents the evolution and technical contributions of our predictive modeling system. It begins by outlining the original plan of implementation inspired by prior literature, proceeds through the practical challenges encountered, and introduces our revised methodology. Furthermore, it highlights the novelty of integrating Bayesian Networks for market factor-based stability analysis, describes our feature set and data preprocessing pipeline, and details the final system implementation.

A. Original Plan of Implementation

While the initial CNN-LSTM architecture showed a thrilling beginning, we encountered some implementation challenges which limited its applicability in the real world. Merging the 1D CNN layer was not easy due to the univariate nature of our input, leading to suboptimal feature extraction and adding unnecessary complexity to the model. Furthermore, projecting the CNN output dimensions onto the needed input shape for the Bidirectional LSTM created architectural inconsistencies that were difficult to rectify without considerable manual intervention. This, along with having not much interpretability and poor scalability to multiple stocks and industries, resulted in a shift of emphasis to a more minimalist and modular architecture. This led to the development of our revised implementation plan, which replaces the CNN layer with a more powerful BiLSTM-only pipeline, introduces empirical constraints via EMA, and allows for automated sector-wise model training for better scalability and stability.

B. Implementation Challenges

But early use revealed some of the constraints. First, using only IBM Close as a feature constrained the model to capture effects from overall market trends or macroeconomic conditions. Second, training the model with scaled price data using MinMax normalization biased the range of output predicted, typically generating unrealistically low values (e.g., 0.05) that did not represent real stock price behavior well, with poor accuracy or MSE score. This revealed issues with the scaling process and feature description. The convergence of training was also weak and random, suggesting a lack of telling patterns in the input when one variable was used. These issues highlighted the need for an improved general multivariate input design and changed preprocessing strategy in order to generate meaningful results.

C. Revised Implementation Strategy

In our revised strategy, we employed a Bidirectional Long Short-Term Memory (BiLSTM) model to enhance predictive accuracy and temporal learning capability for stock price forecasting. The data pipeline begins with an 80:20 train-test split of historical stock prices, followed by normalization using the MinMaxScaler. For each stock, we constructed input sequences with a 60-day lookback period, enabling the model to capture short-term associations. The BiLSTM model—stacked layers with dropout regularization—was trained using the Adam optimizer and mean squared error loss for 12 epochs. The model was rolled out on over 50 stocks across five broad market sectors, with models and scalers saved for modular deployment and reuse.

To add stability and realistic projections, we added an empirical constraint in terms of the 60-day Exponential Moving Average (EMA). Model output was limited to a ± 10 percent range about the EMA to avoid overfitting on outlying data and remain aligned with market movement. We further automated sector-by-sector model testing and training and accumulated predicted values into an aggregated summary table sorting stocks by projected return. This method not only brings domain-knowledge based reasoning and interpretability to the deep learning model but also enables scalable and risk-sensitive investment decision-making.

D. Data and Feature Set

Our dataset includes daily stock price data retrieved from the Alpha Vantage API for over 50 high-performing stocks across five primary sectors: technology, medicine, industrial, finance, and consumer discretionary. For each stock, we retrieved historical data including open, high, low, close, and volume values. To augment the predictive power of our model, we crafted a feature set that includes technical indicators such as moving averages (MA10, MA50, MA100), exponential moving averages (EMA7, EMA14, EMA30, EMA60), and daily returns. We selected these features to include short-term trends along with longer-term momentum in order to provide a more granular view of the price action. The data was cleaned, normalized using MinMaxScaler, and reshaped into fixed-length lookback windows of 60 days as input sequences for our LSTM-based prediction model. This feature engineering step gave the model a rich, temporally-aware representation of each stock's previous performance.

IV. Novelty

One of the significant contributions of this paper is the proposed integration of Bayesian Networks in representing the probabilistic relationship between external finance indicators and stock price stability. While the deep learning model provides next-day price predictions, it is un-interpretable and cannot provide quantification of uncertainty or risk. To compensate for that, we propose a Bayesian reasoning layer that analyzes the effect of external market states on the coherence of predicted price patterns.

The first task in constructing the Bayesian Network is the calculation of Pearson correlation scores between each external feature and target variable. The correlation coefficients help to unveil the most informative variables and identify nodes that must be connected in the Bayesian graph. Features correlating more to price movement take priority in the network structure.

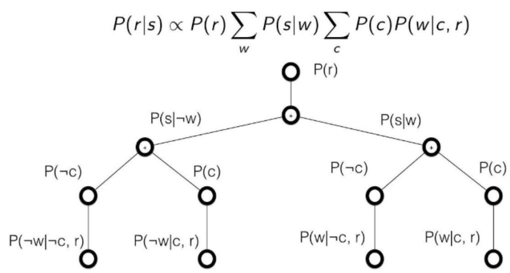

Fig. 2. BN Architecture

The Bayesian Network will determine the risk level of the stock from current market conditions. Once the BiLSTM model has produced a predicted price, the Bayesian layer will determine whether the current market factors support or reject the accuracy of that prediction. This combination of data-driven forecasting and probabilistic reasoning enhances decision-making transparency and allows the model to not only act as a predictive model but also as a risk-aware recommender.

A. Implementation of this Novelty

Our pipeline begins by pulling significant market-wide and sectoral indicators from the Yahoo Finance and Federal Reserve Economic Data (FRED) APIs. They include the SP 500 Index (SP500), Technology Sector ETF (XLK), Volatility Index (VIX), credit spread (BAA–AAA yield difference), 10-Year Treasury Yield, and the Consumer Price Index (CPI). For each stock in the user portfolio, we also compute internal indicators such as rolling volatility, price momentum, daily returns, and trading volume changes.

Each characteristic is discretized into probability bins relative to previous quantiles or empirically determined thresholds. In order to estimate a Conditional Probability Table (CPT), we have a getcptvalue function converting the most recent feature values relative to their thresholds into stability scores. These are weighted by their Pearson correlation with actual stock returns and normalized across all factors. To realize non-linear decision boundaries and preserve valuable variability in the output, we apply a hyperbolic tangent transformation and scale the risk factor onto the [0,1] interval.

Finally, each stock is classified as Stable, Moderate, or Risky based on this risk score, and the price forecast by LSTM is also modified to reflect risk-sensitive investment decision. The approach allows us to maintain interpretability while incorporating expert-informed probabilistic reasoning and dynamic economic feedback into our overall stock evaluation process. The resulting modified predictions and risk levels are combined into a portfolio-level summary for facilitating user decision-making.

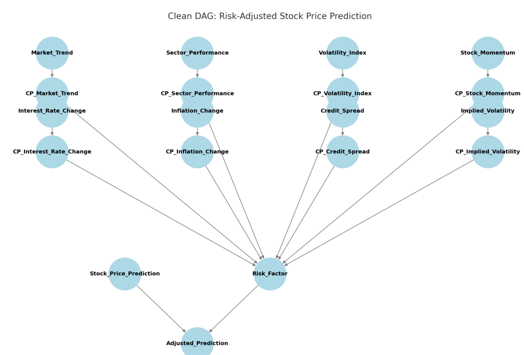

Fig. 3. Directed Acyclic Graph

V. Results and Discussions

A. Results

The BiLSTM model performed well in predicting MSFT stock closing price, as shown in Fig. 5. The predicted price series accurately tracks the actual market trend over a multi-year horizon, picking up long-term momentum and short-term fluctuation. Such alignment indicates the model's ability to learn sequential relationships and non-linear patterns from past price data through the utilization of a 60-day lookback window. In addition, the model also generalizes strongly between market cycles—demonstrated through its sound tracking in both up bull rallies and market downturns. The slight discrepancies seen at steep peaks and troughs can be accounted for by market surprises or flash volatilities, which are by nature difficult for any model to anticipate with absolute certainty. However, the overall predictive consistency of the BiLSTM upholds its potential as a core forecasting instrument in finance applications.

This was supplemented by the Bayesian Network-based risk module, which provided an interpretability layer over the otherwise black-box deep learning predictions. As shown in Fig. 6, the model estimated a "Moderate" level of risk

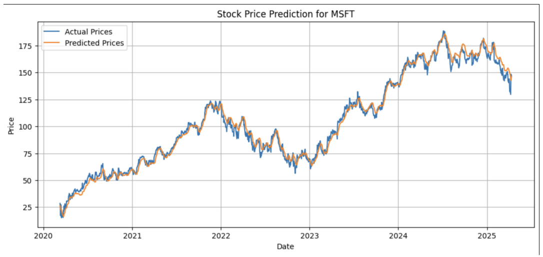

Fig. 4. BiLSTM Stock Prediction

for all five stocks under consideration—AAPL, MSFT, JNJ, GILD, and CAT—based on their macroeconomic exposure and technical indicators. The calculated risk factors fluctuated closely around 0.33, a threshold in our framework that separates "Risky" from "Moderate" levels. These risk scores are computed by a weighted sum of the external variables of VIX movement, credit spread behavior, CPI movement, and sector performance, each examined via a CPT-inspired methodology. The result is that although the model forecast bullish momentum in some stocks, the external financial situation remained cautiously neutral to account for the moderate categorization.

	Stock	Current_Price	LSTM_Prediction	Risk_Adjusted_Price	Risk_Level	Risk_Factor
0	AAPL	198.15	199.128377	65.936751	Moderate	0.331127
1	MSFT	388.45	360.436035	120.232988	Moderate	0.333576
2	JNJ	151.73	146.547729	48.311335	Moderate	0.329663
3	GILD	103.63	101.063774	33.049698	Moderate	0.327018
4	CAT	293.45	304.398191	100.328220	Moderate	0.329595

Fig. 5. Risk Assessment with BN

The incorporation of this Bayesian reasoning layer allowed not just post-hoc verification of LSTM outputs but also actionable investment insight via the risk-adjustment of raw prediction. For instance, MSFT's raw predicted price of 360.43 was risk-adjusted to 120.23, significantly lower, in deference to high volatility and systemic uncertainty in spite of positive historical trends. Similarly, AAPL's LSTM forecast of 199.13 was revised to 65.93, driven by its sensitivity to outside stressors like tech sector performance and inflation fluctuations. This re-contextualization bridges predictive modeling and decision-making responsibility, enabling risk-aware strategies. In essence, the hybrid solution demonstrates how quantitative forecasts can be responsibly interpreted within the context of real-world financial volatility.

B. Challenges

Despite the effectiveness of the hybrid model combining BiLSTM-based forecasting with Bayesian risk reasoning, several implementation challenges and limitations were encountered throughout the research process.

The initial architecture, based on previous CNN-LSTM architectures, was intended to use convolutional layers for extracting spatial features from univariate time series. But, integrating 1D CNNs into a univariate forecasting setup posed significant challenges. The dimensionality alignment of the CNN output and LSTM input layers was not straightforward, leading to shape mismatches and training instability. Additionally, the inclusion of CNN did not yield a significant increase in predictive precision and ultimately led to an altered framework that focused on mere Bidirectional LSTM (BiLSTM) networks. This change made the pipeline easier to simplify and enhance temporal learning capabilities without unnecessary complexity.

Another major issue was the preparation of external financial metrics for the Bayesian Network. These features, including volatility indices, credit spreads, and sector trends, had to be discretized into categorical bins in order to construct Conditional Probability Tables (CPTs). The binning step, while necessary for probabilistic reasoning, added some subjectivity and possibly lost high-granularity information in continuous variables. Also, statistical representativeness of CPTs required an appropriate quantity and variety of past data, which were not always present for all indicators.

One of the intrinsic drawbacks of the current framework is decoupling of the risk assessment and prediction steps. The deep learning model and Bayesian Network execute in parallel, with the Bayesian layer providing a post-hoc explanation of the predicted price against the current market conditions. This does give interpretability but fails to allow the risk signals to influence the calibration or training of the deep learning model. This seclusion limits the learning of the model in a risk-sensitive fashion and prohibits potential opportunities for simultaneous optimization of prediction performance and risk sensitivity.

Lastly, even though the model has been cross-tested on a range of stocks from key sectors, parallel training and testing of multiple models remains computationally expensive. Even though automation scripts were developed to automate this effort, scaling the framework to extend to real-time prediction, live retraining, or additional assets would require system optimization and supporting infrastructure.

These are challenges that provide opportunities for future work, such as designing end-to-end trainable systems where probabilistic reasoning is an objective of learning, improving data preprocessing pipelines, and improving model deployability in real trading environments.

VI. Future Scope

The current research offers a sound foundation for hybrid stock prediction models using deep learning and probabilistic reasoning. Several directions remain available for exploration to enhance both the predictive performance and practical applicability of the provided framework.

One of these development areas is integrating the Bayesian Network into the BiLSTM learning loop. Today, the Bayesian layer is a standalone post-hoc risk estimator independent of the prediction model. Future work can explore architectures allowing bidirectional information flow—where risk signals from the Bayesian layer regulate model learning through uncertainty-guided loss functions or attention. This would facilitate joint optimization, reconciling the model's prediction goals with risk awareness and enhancing its fitness for decision-making under high stakes.

The second promising direction is the exploration of novel predictive models beyond the current BiLSTM architecture. While BiLSTMs excel at modeling temporal dependencies, newer models such as Temporal Fusion Transformers (TFT), Graph Neural Networks (GNNs), and hybrid attention-based networks offer greater interpretability and integration of heterogeneous data sources. They can enhance predictive power, especially in highly dynamic financial circumstances, and might provide better integration with exogenous indicators.

Another potential enhancement is expanding the model's input space beyond traditional technical metrics. Including multivariate features such as sentiment analysis of financial news, macroeconomic information, earnings call transcripts, and geopolitical indicators can provide more contextual information. Making use of natural language processing (NLP) models and alternative data sources can enhance forecast accuracy significantly, especially in high-volatility or sentiment-driven markets.

In addition, the application of this model in an inference-real time environment has important practical applications. Online data streams integration and real-time price forecasting combined with real-time risk measurement can make the system a decision support tool for traders, analysts, and financial planners. A user-interactive dashboard based on the model outputs could provide user interaction, transparency, and faster responses to market activity.

In brief, future work can enhance the existing architecture by building a more tightly coupled predictive-risk pipeline, broadening the range of informative features, enabling real-time deployment, and ultimately expanding the framework for general portfolio optimization.

VII. Conclusion

This paper proposes a hybrid portfolio optimization method merging the sequential learning capacity of Bidirectional Long Short-Term Memory (BiLSTM) neural networks with interpretability and probabilistic reasoning offered by Bayesian Networks. Our proposed model successfully alleviates the flaws of traditional finance models by applying both historical stock trends and current macroeconomic markers to produce not only accurate price forecasts but also risk-adjusted recommendations. The BiLSTM model demonstrated a high predictive power, as per its strict correspondence with real-world market trends for MSFT stock, etc. Meanwhile, the Bayesian Network layer gave an important interpretative contribution by quantifying the effect of market volatility, credit spreads, and other system variables on stock stability.

By combining deep learning with probabilistic inference, the research pushes the class of intelligent financial decision-making systems forward. The system offers improved transparency of predictions, enables investor-level risk calibration, and offers modular scalability across market domains. Although the issues of deployment at real-time, coupled learning between prediction and risk, etc., remain to be addressed, the model serves as a good foundation for dynamic and interpretable financial modeling breakthroughs in the future. Lastly, this research emphasizes the necessity of balancing predictability performance and interpretability in building trustworthy AI systems for high-risk applications like finance.

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