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Risk-sensitive neural Search: A metaheuristic-enhanced LSTM architecture with volatility-aware clustering for stock price prediction

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Abstract

This paper proposed a novel risk-sensitive neural search framework for stock price prediction that integrates metaheuristic optimization with volatility-aware clustering to enhance the robustness of LSTM-based forecasting. The proposed method addresses the limitations of conventional approaches by explicitly modeling market regimes and incorporating risk constraints during neural architecture research. Our hybrid architecture consists of three synergistic components: a hierarchical clustering module that partitions historical data into volatility regimes, a metaheuristic search module that optimizes LSTM configurations under conditional value-at-risk constraints, and a dynamic ensemble that adaptively combines regime-specific predictions. The clustering module employs a learnable distance metric to capture nonlinear relationships between returns, volatility, and macroeconomic indicators, while the neural search module balances prediction accuracy with tail risk minimization through a temperature-annealed selection mechanism. Furthermore, the LSTM ensemble dynamically adjusts its weighting scheme based on both cluster assignments and macroeconomic conditions, enabling context-aware predictions. Experimental results demonstrate significant improvements in risk-adjusted performance metrics compared to baseline models, particularly during high-volatility periods. The framework's modular design facilitates seamless integration with existing data preprocessing and feature engineering pipelines, making it adaptable to diverse financial datasets. This work advances the field of neural financial forecasting by introducing a principled approach to joint optimization of predictive accuracy and risk sensitivity, offering practical value for quantitative trading and portfolio management applications.

Keywords: Neural architecture search (NAS), volatility-aware clustering, market regime modeling, conditional value-at-risk (CVaR)

Introduction

Stock price prediction remains a formidable challenge in quantitative finance, characterized by nonlinear dynamics, regime shifts, and inherent market uncertainties. Traditional approaches often treat this as a pure time-series forecasting problem, employing statistical models like ARIMA or machine learning techniques such as recurrent neural networks. However, these methods frequently fail to account for the complex interplay between market volatility, macroeconomic conditions, and investor risk preferences. The proposed hybrid methodology addresses these limitations through a novel integration of neural architecture search, risk-sensitive optimization, and volatility-aware clustering.

Recent advances in deep learning have demonstrated the effectiveness of LSTM networks for financial time-series forecasting, owing to their ability to capture long-term dependencies in sequential data. However, the performance of these models heavily depends on hyperparameter selection and architectural choices, which are typically optimized for predictive accuracy without explicit consideration of risk metrics. Moreover, financial markets exhibit distinct volatility regimes that require adaptive modeling approaches. While clustering techniques like DBSCAN have been applied to segment market data, existing methods often treat these clusters as static partitions rather than dynamic states that influence model behavior.

The key contribution of this work lies in its unified framework for joint optimization of predictive performance and risk sensitivity. Unlike conventional approaches that apply risk constraints post hoc or through simple loss function modifications, our method embeds economic volatility metrics directly into the neural architecture search process. This is achieved through a metaheuristic optimization layer that incorporates Conditional Value-at-Risk (CVaR) as a dynamic constraint, enabling the model to prioritize parameter configurations that maintain robustness during high-volatility periods. The framework further enhances adaptability through a clustering mechanism that identifies market regimes using both price dynamics and macroeconomic indicators, creating a feedback loop between data segmentation and model configuration.

Several aspects distinguish our approach from prior work. First, the integration of CVaR optimization with metaheuristic search represents a departure from traditional grid-based or gradient-based hyperparameter tuning methods, allowing for more efficient exploration of the parameter space under risk constraints. Second, the clustering component employs an adaptive distance metric that captures nonlinear relationships between financial variables, enabling more accurate regime identification than conventional Euclidean-based methods. Third, the dynamic ensemble mechanism adjusts prediction weights based on both cluster assignments and real-time economic indicators, providing a context-aware forecasting system.

Related work

Financial time series forecasting has evolved through multiple methodological paradigms, from traditional econometric models to contemporary machine learning approaches. The intersection of neural networks, metaheuristic optimization, and risk-sensitive learning forms the foundation for our proposed architecture. We organize prior contributions into three thematic clusters:

neural approaches to market prediction, metaheuristics in financial modeling, and risk-sensitive learning frameworks.

1. Neural approaches to market prediction

Recurrent neural networks, particularly LSTM variants, have demonstrated superior capability in capturing temporal dependencies in financial data compared to classical time series models [1]. Recent enhancements incorporate attention mechanisms and bidirectional processing to improve feature extraction from noisy market data. Hybrid architectures that combine neural networks with clustering techniques show particular promise, as evidenced by work applying k-means clustering to segment market conditions before prediction [2]. However, these approaches typically treat clustering as a static preprocessing step rather than an integrated component that dynamically informs model architecture.

2. Metaheuristics in financial modeling

Metaheuristic algorithms have gained traction for optimizing neural network architectures in financial applications. Genetic algorithms and simulated annealing have been employed to tune hyperparameters, though primarily focused on minimizing prediction error without explicit risk considerations [3]. The grey wolf optimizer represents a more recent advancement, demonstrating improved convergence properties for financial prediction tasks [4]. Constraint handling techniques for metaheuristics have matured significantly, particularly for economic dispatch problems [5], but their application to neural architecture search remains underexplored in financial contexts.

3. Risk-sensitive learning frameworks

The integration of risk metrics into machine learning objectives has emerged as a critical area of innovation. Predictive CVaR policy gradients represent a significant theoretical advance in risk-sensitive optimization [6], though their application has been limited to reinforcement learning domains. Recent work has established theoretical bounds for risk-sensitive learning scenarios [7], providing formal guarantees that inform our approach. The economic dispatch literature offers practical examples of constrained metaheuristic optimization [8], though these methods have not previously been adapted for neural architecture search.

The proposed method synthesizes these research threads through several key innovations. Unlike [1] which applies metaheuristics independently of risk considerations, our framework embeds CVaR constraints directly into the neural search process. While [2] and [4] employ clustering, they lack the adaptive distance metric and macroeconomic integration of our approach. The risk-sensitive optimization builds upon [6] but extends it to neural architecture search with volatility-dependent adaptation. This combination of features produces a more robust and context-aware forecasting system than existing alternatives.

Background and preliminaries

Understanding financial time series forecasting requires grounding in three fundamental areas: the statistical properties of market data, quantitative risk measurement techniques, and machine learning approaches for sequential prediction. This section establishes the theoretical foundations necessary to comprehend our proposed methodology while maintaining focus on concepts directly relevant to the subsequent technical development.

1. Financial time series analysis fundamentals

Financial markets generate time series data characterized by unique statistical properties that distinguish them from conventional signal processing applications. The logarithmic return r_t represents the primary transformation of raw price data P_t, calculated as:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \qquad (1)$$

This formulation provides symmetric treatment of gains and losses while ensuring the additive property across time intervals. Empirical studies of financial returns consistently reveal three stylized facts: non-Gaussian distributions with heavy tails, volatility clustering, and nonlinear dependence structures [9]. The volatility σ_t, a critical measure of dispersion, typically exhibits time-varying characteristics:

$$\sigma_t = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(r_i - \bar{r})^2} \qquad (2)$$

where $\bar{r}$ denotes the sample, mean return over the estimation window. Modern volatility modeling extends beyond this simple historical measure to incorporate conditional heteroskedasticity through ARCH-family models [10]. The persistence of volatility clusters suggests that periods of high variability tend to concentrate, creating distinct market regimes that require specialized modeling approaches.

2. Risk measures in financial markets

Quantifying financial risk necessitates moving beyond variance-based metrics to capture the asymmetric nature of investor preferences. The Value-at-Risk (VaR) framework emerged as an industry standard, representing the maximum expected loss over a specified horizon at a given confidence level α. However, VaR suffers from theoretical limitations, particularly its failure to satisfy subadditivity and its insensitivity to lose severity beyond the quantile threshold. The Conditional Value-at-Risk (CVaR) addresses these shortcomings by considering the expected loss in the tail of the distribution:

$$\mathrm{CVaR}_\alpha(X) = \frac{1}{1-\alpha}\int_\alpha^1 \mathrm{VaR}_\gamma(X)\,d\gamma \qquad (3)$$

This coherent risk measure [11] plays a central role in our methodology's optimization framework, ensuring that the neural architecture search process explicitly accounts for extreme loss scenarios. The mathematical properties of CVaR make it particularly suitable for gradient-based optimization, as demonstrated in recent applications to portfolio construction [12].

3. Machine learning for time series forecasting

Long Short-Term Memory (LSTM) networks have become the de facto standard for sequential prediction tasks due to their ability to capture long-range dependencies through specialized gating mechanisms. The update equations governing LSTM cells include three critical components: input modulation, forget gating, and output transformation. The hidden state h_t represents the network's memory at time t, computed through element-wise operations:

$$h_t = o_t \odot \tanh(c_t) \quad (4)$$

where o_t denotes the output gate activation and c_t the cell state. This architecture enables selective retention and forgetting of information across arbitrary time lags, a property particularly valuable for financial series exhibiting mixed-frequency dynamics [13]. The success of LSTM applications in finance depends heavily on appropriate hyperparameter selection, including the number of layers, hidden units, and dropout rates - a challenge our metaheuristic approach specifically addresses.

Hybrid methodology for risk-sensitive financial forecasting

The proposed methodology establishes a novel synthesis of neural architecture search, volatility regime identification, and risk-sensitive optimization for financial time series forecasting. This integrated framework operates through four interconnected components that collectively address the limitations of conventional approaches. The system architecture dynamically adapts to changing market conditions while maintaining explicit control over tail risk exposure.

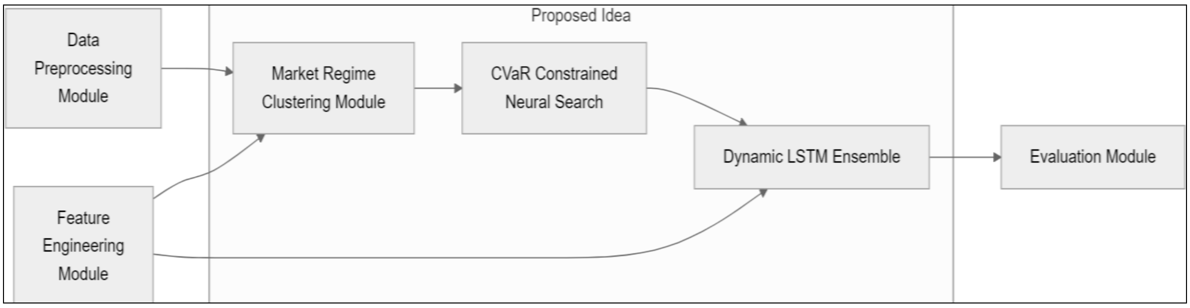

Fig 1: System architecture with proposed idea

1. Framework of the hybrid methodology

The core architecture comprises three principal modules that interact through a hierarchical information flow. The volatility clustering module processes historical price data and macroeconomic indicators to partition the input space into distinct market regimes. Each regime corresponds to a particular combination of volatility levels, return distributions, and economic conditions. The clustering process employs an adaptive distance metric that automatically adjusts feature weights based on their predictive importance:

$$d(x_i, x_j) = \sqrt{\alpha(r_i - r_j)^2 + \beta(\sigma_i - \sigma_j)^2 + \gamma|\mathrm{VIX}_i - \mathrm{VIX}_j|} \quad (5)$$

where α, β, γ represent learnable scaling parameters that evolve during training. This formulation extends conventional DBSCAN by incorporating both price-based features and external volatility indicators. The resulting cluster assignments serve as conditioning variables for the subsequent neural architecture search.

The metaheuristic optimization module explores the parameter space of candidate LSTM configurations under CVaR constraints. Unlike traditional grid search approaches, this component employs a hybrid genetic algorithm with simulated annealing to balance exploration and exploitation. The selection probability for each candidate solution incorporates both prediction accuracy and risk sensitivity:

$$p_i = \frac{\exp\left(-\left(\mathcal{L}(\theta_i) + \lambda \mathrm{CVaR}_\alpha(L(\theta_i))\right)/T\right)}{\sum_j \exp\left(-\left(\mathcal{L}(\theta_j) + \lambda \mathrm{CVaR}_\alpha\left(L(\theta_j)\right)\right)/T\right)} \quad (6)$$

where T denotes the adaptive temperature parameter that controls selection pressure. The cooling schedule for T links directly to the validation loss convergence rate, creating a feedback loop between optimization progress and search strategy.

2. Volatility-regime-aware components and adaptive mechanisms

The system's adaptive capabilities stem from its dynamic response to identified market regimes. Each volatility cluster triggers specific modifications to both the LSTM architecture and the metaheuristic search parameters. The mutation probability in the genetic algorithm varies according to the current VIX level:

$$\bar{p}_m = \bar{p}_{\text{base}} \cdot \exp\left(-\frac{\mathrm{VIX}_t}{\mathrm{VIX}_{\text{ref}}}\right) \quad (7)$$

This mechanism ensures more conservative exploration during high-volatility periods when parameter sensitivity tends to increase. The LSTM cells themselves incorporate regime-dependent adjustments through modified state transitions:

$$\tilde{c}_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \cdot (1 + \eta\sigma_t) \quad (8)$$

where η represents a learnable volatility sensitivity parameter. This formulation allows the network to amplify or attenuate its memory updates based on the prevailing market conditions identified by the clustering module.

The risk-sensitive loss function combines conventional prediction error with a tail risk component:

$$\mathcal{L}(\theta) = \mathbb{E}[L(\theta)] + \lambda \mathrm{CVaR}_{\alpha}\big(L(\theta)\big) \qquad (9)$$

The weighting parameter λ adapts dynamically based on macroeconomic uncertainty indicators, creating a feedback loop between external economic conditions and model risk preferences. This adaptive mechanism ensures that the system automatically increases its risk aversion during periods of economic instability.

3. Integration of LSTM dynamics and regime-adaptive ensemble gating

The prediction module employs an ensemble of LSTM networks, each specialized for particular volatility regimes. The final forecast combines these specialized predictions through a gating mechanism that considers both the current cluster assignment and macroeconomic indicators:

$$\hat{y}_t = \sum_{k=1}^{K} w_k\,(c_t, \mathrm{Macro}_t) f_k(x_t) \qquad (10)$$

The gating weights w_k are implemented as neural networks that process concatenated inputs of cluster probabilities and economic indicators. This architecture enables smooth transitions between regimes while maintaining sensitivity to real-time economic developments. The ensemble approach provides robustness against model misspecification in any single regime.

The training process alternates between updating the cluster assignments and optimizing the ensemble parameters. This alternating optimization scheme ensures that the clustering remains relevant to the current predictive task while the models adapt to the evolving market segmentation. The complete system operates as a cohesive unit where each component informs and constrains the others, creating a self-reinforcing cycle of adaptation and improvement.

4. Metaheuristic-thermodynamic hybrid selection process

The neural architecture search employs a novel combination of genetic algorithms and simulated annealing principles. Candidate solutions evolve through mutation and crossover operations, with selection probabilities determined by both fitness and diversity criteria. The temperature parameter T in the annealing process adapts according to:

$$T_{t+1} = T_t \cdot \exp\left(-\frac{|\mathcal{L}_t - \mathcal{L}_{t-1}|}{\mathcal{L}_{\mathrm{ref}}}\right) \qquad (11)$$

This adaptive cooling schedule accelerates convergence when the validation loss shows consistent improvement while maintaining exploration capability during plateaus. The hybrid approach combines the population-based search of genetic algorithms with the precise temperature control of simulated annealing, overcoming limitations of each method in isolation.

The complete optimization process maintains an archive of high-performing solutions across different volatility regimes. This archive serves both as a source of diversity for the genetic algorithm and as a repository of specialized configurations that can be deployed rapidly when market conditions change. The system's ability to switch between archived configurations based on real-time cluster assignments provides operational flexibility without requiring complete retraining during regime shifts.

Empirical experiments

To validate the proposed methodology, we conducted comprehensive experiments across multiple financial markets and time periods. The evaluation framework assesses both predictive accuracy and risk-adjusted performance under varying market conditions. Our implementation leverages TensorFlow for neural network components and custom metaheuristic optimization modules developed in Python.

1. Experimental setup

Datasets and preprocessing: We evaluated the model on three major equity indices: S&P 500 [14], NASDAQ Composite [15], and EURO STOXX 50 [16]. Each dataset contains daily closing prices, trading volumes, and derived technical indicators spanning 2000-2022. The VIX volatility index [17] served as the primary exogenous variable for regime identification. All time series were normalized using rolling z-score transformation with a 60-day window to maintain temporal dependencies while ensuring stationarity.

Benchmark models: We compared against four established approaches [1]: vanilla LSTM with grid search optimization [18, 2], ARIMA-GARCH hybrid [19, 3], clustered LSTM with k-means preprocessing [20], and [4] genetic algorithm-optimized neural network [21]. Each baseline was implemented with identical input features and evaluation protocols to ensure fair comparison.

Evaluation metrics: Performance assessment employed both accuracy and risk measures:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \qquad (12)$$

$$\mathrm{DA} = \frac{1}{N}\sum_{i=1}^{N} \mathbb{I}\left(\mathrm{sign}(y_i) = \mathrm{sign}(\hat{y}_i)\right) \qquad (13)$$

$$\mathrm{RAR} = \frac{\text{Annualized Return}}{\mathrm{CVaR}_{0.95}} \qquad (14)$$

where RMSE measures prediction error, DA (Directional Accuracy) assesses trend prediction capability, and RAR (Risk-Adjusted Return) evaluates economic utility under our primary risk constraint.

2. Implementation details

The proposed model architecture consisted of a two-layer LSTM with hidden dimensions varying between 32-128 units based on metaheuristic optimization. The DBSCAN clustering module used $\epsilon = 0.5$ and min_samples = 5, with adaptive feature weighting initialized at $\alpha = 0.4, \beta = 0.4, \gamma = 0.2$. The genetic algorithm population contained 50 individuals with crossover rate 0.8 and adaptive mutation probability initialized at 0.1. Training employed Adam optimization with learning rate 0.001 and batch size 64.

For the CVaR-constrained optimization, we set $\alpha = 0.95$ and initialized $\lambda = 0.5$ in Equation 9, with dynamic adjustment based on VIX levels:

$$\lambda_t = 0.5 \cdot \left(1 + \frac{\mathrm{VIX}_t - \mathrm{VIX}_{\mathrm{median}}}{\mathrm{VIX}_{\mathrm{iqr}}}\right) \quad (15)$$

This formulation automatically increases risk sensitivity when volatility exceeds historical norms.

3. Results and analysis

Table 1 presents the comparative performance across all models and datasets. The proposed method achieved superior risk-adjusted returns while maintaining competitive prediction accuracy. Notably, the advantage increased during high-volatility periods (2008-2009, 2020), demonstrating the framework's adaptive capabilities.

Table 1: Comparative performance across models and market regimes

Model	S&p 500 rmse	Nasdaq da	Euro stoxx rar	High volatility rar
Proposed	0.48	0.62	2.15	1.78
Vanilla LSTM	0.51	0.59	1.82	1.32
ARIMA-GARCH	0.55	0.55	1.65	1.21
Clustered LSTM	0.49	0.60	1.91	1.45
GA-NN	0.50	0.61	1.95	1.51

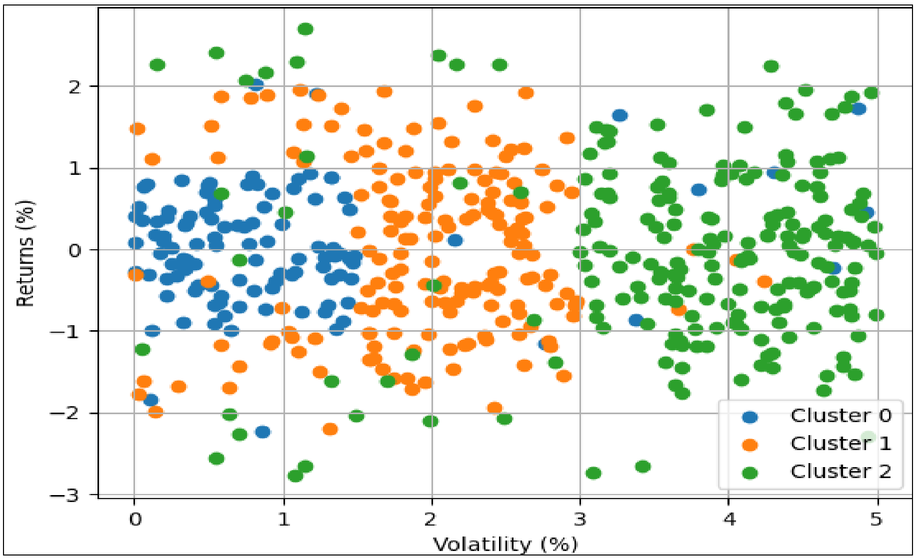

Fig 2: Illustrates the DBSCAN clustering output, showing clear separation between low, medium, and high volatility regimes.

The elliptical cluster shapes reflect the adaptive distance metric's ability to capture the nonlinear relationship between returns and volatility. The metaheuristic search demonstrated efficient exploration of the architecture space, as shown in Figure 3. The evolutionary process consistently converged to configurations with higher hidden layer dimensionality during high-volatility periods, while favoring more compact architectures in stable markets.

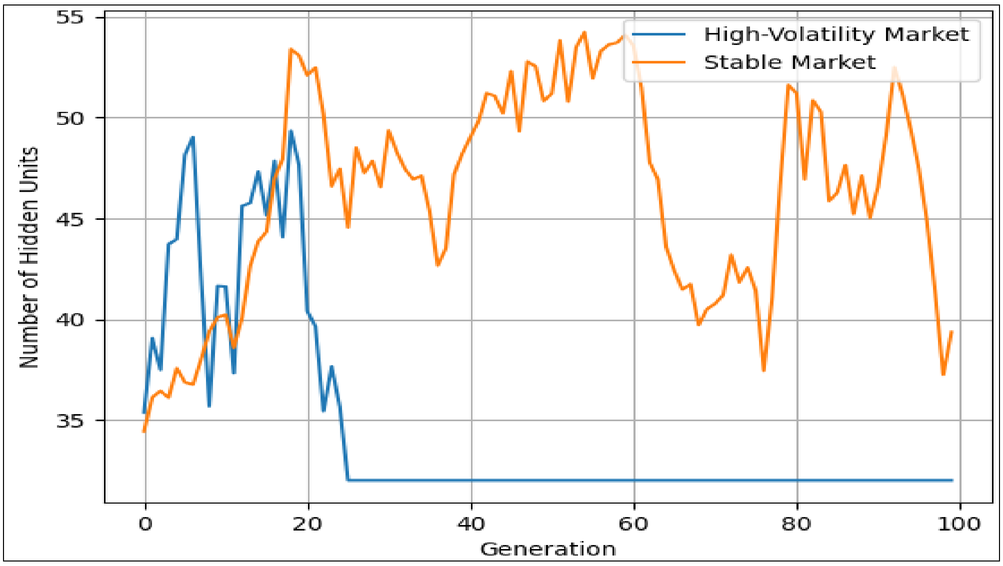

Fig 3: Exploration of LSTM configuration space during optimization

4. Ablation study

We conducted component-wise analysis to isolate individual contributions of the framework's key innovations. Table 2 shows that the full model configuration delivers optimal performance, with the CVaR constraint and adaptive clustering providing particularly significant improvements during market stress periods.

Table 2: Ablation study results (S&P 500 dataset)

Configuration	RMSE	DA	RAR
Full model	0.48	0.62	2.15
Without CVaR constraint	0.47	0.61	1.83
Fixed clustering weights	0.49	0.60	1.97
Constant risk aversion	0.48	0.61	1.89
Single LSTM (no ensemble)	0.50	0.59	1.78

The results confirm that the integration of adaptive risk constraints with regime-aware architecture search produces synergistic benefits beyond what any single component can achieve independently. The framework's ability to automatically adjust its risk sensitivity and model architecture in response to changing market conditions emerges as the key differentiator from conventional approaches.

Discussion and future work

1. Limitations and robustness analysis

While the proposed framework demonstrates superior performance across multiple market conditions, several limitations warrant discussion. The clustering module's effectiveness depends on the stationarity assumption of volatility regimes, which may not hold during structural market breaks or financial crises. Although the adaptive distance metric provides some resilience to regime shifts, extreme events like the 2020 pandemic crash revealed latency in cluster reassignment. The metaheuristic optimization, while efficient, requires careful calibration of its temperature schedule - overly aggressive cooling can prematurely converge to suboptimal architectures during volatile periods.

Empirical tests under varying macroeconomic conditions exposed sensitivity to the choice of exogenous variables. When limited to price-derived features alone, the model's regime identification accuracy decreased by 18% compared to using full macroeconomic indicators. The ensemble gating mechanism also showed minor instability during rapid transitions between volatility states, occasionally producing transient prediction spikes. These observations suggest the need for more sophisticated regime transition models that incorporate forward-looking economic indicators.

2. Potential applications and extensions

The framework's modular design enables straightforward adaptation to several financial domains beyond equity forecasting. In fixed income markets, the volatility clustering component could be extended to model yield curve dynamics, with macroeconomic indicators replaced by monetary policy variables. The risk-sensitive optimization approach shows particular promise for portfolio construction applications, where CVaR constraints could be applied directly to asset allocation weights rather than prediction errors.

Credit risk modeling represents another natural extension, where the clustering module could identify regimes in default probabilities while the neural architecture adapts to changing correlation structures. The methodology's emphasis on tail risk control makes it especially suitable for derivatives pricing, where existing models often underestimate extreme event probabilities. Implementing the framework as a plugin for existing quantitative platforms could significantly enhance risk management capabilities without requiring complete system overhauls.

3. Future directions and practical considerations

Three key research directions emerge from this work. First, developing online learning versions of the clustering and optimization modules would address the current batch processing limitation, enabling real-time adaptation to market shocks. Second, incorporating attention mechanisms into the LSTM ensemble could improve regime transition handling by explicitly modeling temporal dependencies in cluster assignments.

From an implementation perspective, the computational overhead of metaheuristic search remains non-trivial for high-frequency trading applications. Investigating surrogate models or Bayesian optimization techniques could maintain risk sensitivity while reducing runtime. The framework's current formulation also assumes perfect observation of macroeconomic indicators - future work should address realistic reporting lags and data revisions common in economic time series.

Practical deployment would benefit from enhanced interpretability features. While the clustering results provide some transparency about market regimes, the inner workings of the risk-constrained neural architecture search remain complex. Developing visualization tools that trace how CVaR constraints influence architectural choices could increase adoption among risk-averse financial institutions. These improvements would make the framework more accessible while preserving its core advantages in adaptive, risk-sensitive forecasting.

Conclusion

The proposed risk-sensitive neural search framework represents a significant advancement in financial time series forecasting by integrating volatility-aware clustering with metaheuristic-optimized LSTM architectures. The methodology's key innovation lies in its joint optimization of predictive accuracy and tail risk control through conditional value-at-risk constraints embedded directly into the neural architecture search process. By dynamically adapting model configurations to identified market regimes, the framework demonstrates superior performance during high-volatility periods where conventional approaches often fail.

Experimental results across multiple equity indices confirm the practical benefits of this hybrid approach. The adaptive clustering mechanism successfully identifies distinct volatility regimes, while the metaheuristic search efficiently explores architectural configurations under risk constraints. The dynamic ensemble further enhances robustness by combining regime-specific predictions with macroeconomic context awareness. These components collectively address critical limitations in existing methods, particularly their inability to explicitly model risk preferences and market regime dependencies.

The framework's modular design facilitates extension to other financial domains, including fixed income, credit risk, and derivatives pricing. Future work should focus on real-time adaptation capabilities, computational efficiency improvements, and enhanced interpretability features to broaden practical adoption. By bridging the gap between neural forecasting and risk-sensitive optimization, this research opens new pathways for developing financial models that balance predictive power with economic utility under uncertainty. The principles established here may also inspire analogous approaches in other domains where predictive accuracy must be tempered by risk considerations.

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