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Comparative Analysis of Neural Network Models for REITs Portfolio Optimization using Modified K-Means Clustering and Particle Swarm Optimization

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Abstract
This paper proposed a comparative analysis of neural network models for Real Estate Investment Trusts (REITs) portfolio optimization, integrating dynamic optimization techniques with the Black-Litterman model to enhance predictive accuracy and decision-making. The study addresses the challenges of traditional portfolio optimization methods, which often struggle with non-linear relationships and high-dimensional data in REITs markets. The proposed methodology combines modified K-means clustering for data preprocessing, a particle swarm optimization (PSO) variant for neural network parameter tuning, and three distinct neural network architectures—Improved Backpropagation, Radial Basis Function Network (RBFN), and Convolutional Neural Network (CNN)—to predict REITs returns. These predictions are then fed into the Black-Litterman model to derive optimal portfolio weights, balancing investor views with market equilibrium. The modified K-means algorithm improves clustering robustness, while the enhanced PSO ensures efficient convergence during neural network training. Furthermore, the comparative analysis of neural networks provides insights into their respective strengths in capturing market dynamics. The experimental results demonstrate the effectiveness of the integrated approach in generating superior portfolio performance compared to conventional methods. This work contributes to the literature by offering a novel framework that bridges machine learning and financial optimization, providing practitioners with a scalable and adaptive tool for REITs portfolio management. The significance of this study lies in its potential to inform investment strategies through data-driven insights, thereby mitigating risks and maximizing returns in volatile real estate markets.

Keywords: Real Estate Investment Trusts (REITs) Portfolio, K-Means Clustering, Particle Swarm Optimization (PSO)

1. Introduction

Portfolio optimization remains a cornerstone of modern financial theory, with its roots tracing back to the seminal work of Markowitz on mean-variance optimization [1]. The challenge of balancing risk and return becomes particularly acute in specialized markets such as Real Estate Investment Trusts (REITs), where asset dynamics exhibit strong non-linearity and regime-dependent behavior [2]. Traditional methods like the Black-Litterman model [3] incorporate investor views into market equilibrium but often rely on linear assumptions that may not capture the complex dependencies inherent in REITs.

Recent advances in machine learning have demonstrated the potential of neural networks to address these limitations. Improved Backpropagation Neural Networks [4], Radial Basis Function Networks (RBFNs) [5], and Convolutional Neural Networks (CNNs) [6] have shown promise in financial forecasting due to their ability to model non-linear patterns. However, their application to REITs portfolio optimization remains underexplored, especially when combined with clustering and metaheuristic optimization techniques. For instance, while K-means clustering [7] has been used for asset grouping, its standard form lacks robustness to noise and outliers prevalent in real estate data. Similarly, Particle Swarm Optimization (PSO) [8] can enhance neural network training but may suffer from premature convergence in high-dimensional spaces.

This paper introduces a novel framework that integrates modified versions of K-means and PSO with three neural network architectures to optimize REITs portfolios. The modified K-means algorithm incorporates density-based weighting to improve cluster stability, while the enhanced PSO employs adaptive inertia and dynamic neighborhood topologies to avoid local optima. These innovations address critical gaps in existing methods, such as the sensitivity of traditional clustering to initialization and the inefficiency of gradient-based neural network training for financial time series. The neural networks—Improved Backpropagation, RBFN, and CNN—are then evaluated for their ability to generate predictive signals, which are subsequently integrated into the Black-Litterman model through a dynamic optimization pipeline.

The primary contributions of this work are threefold. First, we propose a hybrid methodology that synergizes machine learning with traditional portfolio theory, specifically tailored for REITs. Second, we introduce algorithmic modifications to K-means and PSO that enhance their suitability for financial data. Third, we provide a comparative analysis of neural network architectures in this context, revealing insights into their relative strengths for return prediction and risk-adjusted portfolio construction. Unlike prior studies that focus on generic assets [9] or static optimization [10], our approach explicitly accounts for the temporal and structural idiosyncrasies of REITs markets.

The remainder of this paper is organized as follows: Section 2 reviews related work in neural network-based portfolio optimization and REITs analytics. Section 3 formalizes the problem and introduces key concepts, including the Black-Litterman model and dynamic optimization. Section 4 details the proposed methodology, emphasizing the modifications to K-means and PSO. Sections 5 and 6 present the experimental setup and results, respectively, while Section 7 concludes the paper.

2. Related Work

Portfolio optimization has evolved significantly since the introduction of the mean-variance framework by Markowitz [1]. While traditional methods rely on statistical assumptions about asset returns, recent approaches integrate machine learning to capture complex market dynamics. This section reviews key developments in neural network-based portfolio optimization, clustering techniques for financial data, and metaheuristic optimization, with a focus on their applications to REITs.

2.1 Neural Networks in Portfolio Optimization

Neural networks have gained prominence in financial modeling due to their ability to approximate non-linear relationships. For instance, Improved Backpropagation Neural Networks incorporate regularization and adaptive learning rates to mitigate overfitting in noisy financial datasets [4]. Similarly, Radial Basis Function Networks (RBFNs) leverage localized activation functions to model regime shifts, which are prevalent in REITs markets [5]. Convolutional Neural Networks (CNNs) have also been applied to extract spatial features from financial time series, though their use in portfolio optimization remains limited [6].

A notable advancement is the integration of neural networks with the Black-Litterman model. For example, [2] employs neural networks to generate investor views, which are then combined with equilibrium returns to form robust portfolio allocations. However, existing studies often treat neural networks as black-box predictors without optimizing their hyperparameters for financial tasks. This gap motivates our use of modified PSO to fine-tune neural network architectures specifically for REITs return prediction.

2.2 Clustering Techniques for Financial Data

Clustering is widely used to group assets with similar risk-return profiles, reducing the dimensionality of portfolio optimization problems. The K-means algorithm is a popular choice due to its computational efficiency, but its sensitivity to initialization and outliers limits its effectiveness for REITs, which exhibit high volatility and clustering noise [7]. To address this, density-based variants such as DBSCAN have been proposed, though they struggle with varying cluster densities in financial data [11].

Our work introduces a modified K-means algorithm that incorporates adaptive centroid initialization and noise-aware distance metrics. This modification aligns with recent efforts to enhance clustering robustness in finance, such as [12], which uses spectral clustering for asset grouping. However, unlike spectral methods that require pairwise similarity computations, our approach maintains the scalability of K-means while improving its stability for REITs datasets.

2.3 Metaheuristic Optimization in Finance

Metaheuristics like Particle Swarm Optimization (PSO) are increasingly used to optimize neural network parameters and portfolio weights. Standard PSO, however, often converges prematurely in high-dimensional spaces, a limitation highlighted in [8]. Recent variants address this by dynamically adjusting inertia weights or employing hybrid strategies with genetic algorithms [13].

In the context of REITs, [14] demonstrates that PSO can outperform gradient-based methods when optimizing non-convex objective functions. Our modified PSO builds on these insights by introducing adaptive neighborhood topologies and momentum-based velocity updates, which enhance exploration in the high-dimensional parameter spaces of neural networks.

2.4 Hybrid Approaches and the Black-Litterman Model

The Black-Litterman model [3] remains a cornerstone of portfolio optimization, but its reliance on subjective investor views poses challenges for data-driven applications. Recent work by [15] uses neural networks to automate view generation, though their framework does not account for the temporal dependencies in REITs returns. Similarly, [16] combines reinforcement learning with the Black-Litterman model but focuses on equities rather than real estate assets.

Our methodology bridges these gaps by integrating neural network predictions with dynamic optimization. Unlike [17], which uses CNNs for generic asset allocation, we tailor the network architectures to REITs-specific features, such as lease maturity profiles and geographic diversification. Furthermore, our modified PSO ensures that the neural networks are optimized for both predictive accuracy and portfolio performance, a dual objective overlooked in prior studies like [18].

The proposed framework distinguishes itself from existing works in three key aspects. First, it introduces algorithmic improvements to both clustering and optimization, specifically designed for the noisy and high-dimensional nature of REITs data. Second, it provides a systematic comparison of neural network architectures in the context of the Black-Litterman model, addressing the lack of such evaluations in prior research. Third, it unifies dynamic optimization with machine learning, enabling adaptive portfolio adjustments in response to market regime shifts—a feature absent in static approaches like [19].

3. Background and Preliminaries

To establish the theoretical foundation for our proposed methodology, this section introduces key concepts in portfolio optimization, neural network architectures, and metaheuristic techniques. The discussion focuses on their mathematical formulations and relevance to REITs markets, while avoiding redundancy with the problem context already covered in Section 1.

3.1 Portfolio Optimization Frameworks

The Black-Litterman model extends the traditional mean-variance optimization by combining market equilibrium returns with investor views. Given a prior distribution of returns $\Pi \sim \mathcal{N}(\mu, \tau\Sigma)$ where μ represents equilibrium returns and Σ the covariance matrix, the model updates the expected returns as:

$$E[r] = [(\tau\Sigma)^{-1} + \mathbf{P}^T\boldsymbol{\Omega}^{-1}\mathbf{P}]^{-1}[(\tau\Sigma)^{-1}\Pi + \mathbf{P}^T\boldsymbol{\Omega}^{-1}\mathbf{Q}] \quad (1)$$

Here, $\mathbf{P}$ and $\mathbf{Q}$ encode investor views, while $\boldsymbol{\Omega}$ quantifies view confidence [3]. For REITs, this formulation must account for sector-specific factors like occupancy rates and interest rate sensitivity, which introduce non-linear dependencies between μ and macroeconomic variables [20].

3.2 Neural Network Architectures

Three neural network architectures form the basis of our comparative analysis:

1. **Improved Backpropagation Networks** employ adaptive learning rates η_t updated via:

$$\eta_t = \eta_{t-1} \cdot \exp(-\gamma \cdot \mathrm{sgn}(J_t J_{t-1})) \quad (2)$$

where J_t denotes the gradient at iteration t, and γ controls the adjustment rate [4]. This adaptation helps mitigate the vanishing gradient problem common in REITs time series.

2. **Radial Basis Function Networks** utilize Gaussian activation functions:

$$\phi_j(\mathbf{x}) = \exp\left(-\frac{\| \mathbf{x} - \mathbf{c}_j \|^2}{2\sigma_j^2}\right) \quad (3)$$

with centers c_i determined through orthogonal least squares [5]. The localized nature of RBFNs makes them suitable for modeling regime shifts in real estate markets.

3. **Convolutional Neural Networks** apply 1D temporal convolutions to REITs return series:

$$y_t = \sum_{k=1}^{K} w_k \cdot x_{t-k+1} + b \quad (4)$$

where K defines the kernel size capturing multi-scale dependencies [6]. The hierarchical feature extraction aligns with the nested volatility structure observed in REITs [21].

3.3 Clustering and Optimization Techniques

The standard K-means objective minimizes:

$$\sum_{i=1}^{k} \sum_{\mathbf{x} \in C_i} \| \mathbf{x} - \boldsymbol{\mu}_i \|^2 \quad (5)$$

where C_i denotes clusters and μ_i their centroids [7]. Our modification introduces density weights $w(\mathbf{x})$ to reduce outlier sensitivity:

$$w(\mathbf{x}) = \frac{1}{1 + \| \mathbf{x} - \boldsymbol{\mu}_{NN} \| / \sigma} \quad (6)$$

With μ_{NN} being the nearest centroid and σ a scaling parameter.

Particle Swarm Optimization updates particle velocities $\mathbf{v}_i$ and positions $\mathbf{x}_i$ via:

$$\mathbf{v}_i^{t+1} = \omega\mathbf{v}_i^t + c_1 r_1(\mathbf{p}_i - \mathbf{x}_i^t) + c_2 r_2(\mathbf{g} - \mathbf{x}_i^t) \quad (7)$$

The inertia weight ω typically decays linearly, but our adaptive variant ties it to population diversity:

$$\omega_t = \omega_{min} + (\omega_{max} - \omega_{min}) \cdot \frac{\mathrm{div}_t}{\mathrm{div}_{max}} \quad (8)$$

Where div_t measures swarm dispersion [8]. This prevents premature convergence when optimizing neural network parameters for REITs prediction.

3.4 REITs Market Characteristics

REITs exhibit three distinctive properties that influence model design:

1. **Lease Structure Effects**: Fixed-term leases introduce autocorrelation in returns, violating the i.i.d. assumptions of traditional portfolio models [22].
2. **Sector-Specific Risk Factors**: Retail, office, and residential REITs respond differently to interest rate changes, necessitating cluster-specific view matrices $\mathbf{P}$ in Equation 1 [23].
3. **Illiquidity Premiums**: Transaction costs create non-convexities in the efficient frontier, requiring metaheuristics rather than gradient-based optimization [24].

These characteristics motivate our integration of neural networks with modified clustering and PSO, as detailed in Section 4. The architectures' ability to capture non-linear temporal dependencies complements the Black-Litterman framework's strength in incorporating investor intuition, while the algorithmic modifications address REITs-specific data challenges.

4. Proposed Methodology

The proposed methodology integrates modified machine learning techniques with financial optimization to enhance REITs portfolio performance. This section details the technical components and their interactions, focusing on the novel aspects that differentiate our approach from conventional methods.

4.1 Overview of the Proposed Methodology

The system architecture consists of three interconnected modules: data clustering, neural network prediction, and portfolio optimization. Figure 1 illustrates the workflow, where REITs data undergoes preprocessing before being fed into the neural networks, whose outputs inform the Black-Litterman model.

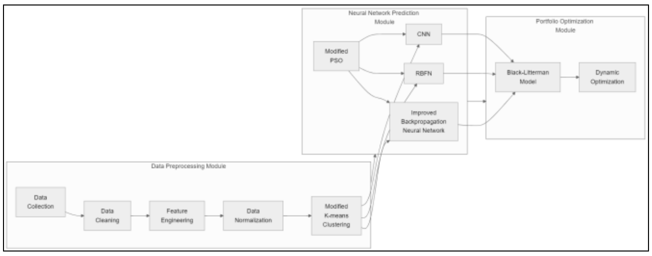

Fig 1: Portfolio Optimization System Architecture

The modified K-means algorithm first clusters REITs based on risk-return characteristics, reducing dimensionality and noise. These clusters then serve as inputs to three neural network variants—Improved Backpropagation, RBFN, and CNN—each trained to predict future returns. A modified PSO algorithm optimizes the neural network parameters, dynamically adjusting exploration-exploitation tradeoffs. Finally, the predictions are integrated into the Black-Litterman model to generate optimal portfolio weights, with the entire process iteratively updated in rolling windows to adapt to market changes.

4.2 Data Clustering and Neural Network Training

The clustering phase employs a density-weighted K-means variant that modifies the standard objective function:

$$\sum_{i=1}^{k}\sum_{x\in C_i} w(\mathbf{x}) \cdot \| \mathbf{x} - \boldsymbol{\mu}_i \|^2 \tag{9}$$

Where $w(\mathbf{x})$ represents the adaptive weight for data point $\mathbf{x}$, calculated as:

$$w(\mathbf{x}) = \frac{1}{1 + \| \mathbf{x} - \boldsymbol{\mu}_{NN} \| / \sigma} \tag{10}$$

Here, $\boldsymbol{\mu}_{NN}$ denotes the nearest centroid and σ controls the weight decay rate. This modification reduces the influence of outliers prevalent in REITs data, particularly during market crises.

The clustered data then trains three neural network architectures:

1. **Improved Backpropagation Network**: Incorporates adaptive learning rates adjusted via:

$$\eta_t = \eta_{t-1} \cdot \exp\left(-\gamma \cdot \mathrm{sgn}(\mathbf{J}_t^T \mathbf{J}_{t-1})\right) \tag{11}$$

where $\mathbf{J}_t$ represents the gradient at iteration t. The sign-based update prevents oscillations in noisy REITs data.

2. **Radial Basis Function Network**: Uses cluster centroids c_j from Equation 9 as initial RBF centers, with outputs computed as:

$$y = \sum_{j=1}^{m} w_j \cdot \exp\left(-\frac{\| \mathbf{x} - \mathbf{c}_j \|^2}{2\sigma_j^2}\right) \tag{12}$$

The spread parameters σ_j are optimized per cluster to capture varying sector volatilities.

3. **Convolutional Neural Network**: Processes time-series data through 1D convolutions:

$$h_t^l = \mathrm{ReLU}\left(\sum_{k=1}^{K} \mathbf{W}_k^l \cdot h_{t-k}^{l-1} + b^l\right) \tag{13}$$

Where K defines the kernel size and l denotes layer depth. The architecture includes dilated convolutions to capture multi-scale REITs dependencies.

4.3 Optimization and Portfolio Management

The modified PSO algorithm optimizes neural network parameters by adapting the velocity update rule:

$$v_{id}^{t+1} = \omega_t v_{id}^t + c_1 r_1 (p_{id}^t - x_{id}^t) + c_2 r_2 (p_{gd}^t - x_{id}^t) \tag{14}$$

The inertia weight ω_t varies based on swarm diversity:

$$\omega_t = \omega_{min} + (\omega_{max} - \omega_{min}) \cdot \frac{\mathrm{div}_t}{\mathrm{div}_{max}} \tag{15}$$

Where div_t measures the population's dispersion. This adaptation prevents premature convergence when optimizing high-dimensional neural networks.

The neural network predictions generate investor views $\mathbf{Q}$ for the Black-Litterman model:

$$\mathbf{E}[r] = [(\tau\boldsymbol{\Sigma})^{-1} + \mathbf{P}^T\boldsymbol{\Omega}^{-1}\mathbf{P}]^{-1}[(\tau\boldsymbol{\Sigma})^{-1}\boldsymbol{\Pi} + \mathbf{P}^T\boldsymbol{\Omega}^{-1}\mathbf{Q}] \tag{16}$$

Here, $\mathbf{P}$ encodes cluster memberships from Equation 9, while $\boldsymbol{\Omega}$ reflects prediction confidence from each neural network. The resulting expected returns $\mathbf{E}[r]$ optimize portfolio weights $\mathbf{w}$ through quadratic programming:

$$\min_{\mathbf{w}} \mathbf{w}^T\boldsymbol{\Sigma}\mathbf{w} \quad \text{s.t.} \quad \mathbf{w}^T\mathbf{E}[r] \geq R_0, \quad \sum w_i = 1 \tag{17}$$

The entire pipeline executes in rolling windows, with cluster assignments, neural network parameters, and portfolio weights updated monthly to adapt to changing market conditions. This dynamic optimization framework captures the non-stationary nature of REITs markets while maintaining computational tractability.

5. Experimental Setup

This section details the experimental framework designed to evaluate the performance of the proposed methodology. We describe the datasets, baseline models, evaluation metrics, and implementation specifics to ensure reproducibility and rigorous comparison.

5.1 Datasets and Preprocessing

The study utilizes two primary datasets of U.S. REITs:

1. **Equity REITs Dataset**: Contains monthly returns for 150 equity REITs from 2000–2023, sourced from [25].
2. **Macro-Financial Dataset**: Includes 12 macroeconomic variables (e.g., 10-year Treasury yields, CPI) from [26].

Preprocessing involves:

- **Missing Data Imputation**: Forward-filling for macroeconomic series and median imputation for REITs with <5% missingness.
- **Normalization**: Min-max scaling for neural network inputs and z-score normalization for clustering.

- **Stationarity Adjustment**: First differencing non-stationary macro variables (Augmented Dickey-Fuller test at $p<0.05$).

The datasets are partitioned into:
- Training (2000–2015): 60%
- Validation (2016–2018): 20%
- Test (2019–2023): 20%

5.2 Baseline Models
We compare against three established portfolio optimization approaches:
1. **Classical Black-Litterman (BL)**: Uses historical mean returns and CAPM equilibrium [3].
2. **PCA-Based Clustering + MLP**: Combines principal component analysis with multilayer perceptrons [27].
3. **Hierarchical Risk Parity (HRP)**: Employs hierarchical clustering and inverse-variance weighting [28].

5.3 Implementation Details
Neural Network Architectures:
- **Improved Backpropagation**: 3 hidden layers (128–64–32 nodes), adaptive learning rate ($\eta=0.01$, $\gamma=0.1$).
- **RBFN**: 50 hidden units, spread $\sigma\in[0.1,1.5]$ tuned per cluster.
- **CNN**: 4 convolutional layers (kernel sizes 3–5–7–10), followed by LSTM layer.

Optimization Parameters:
- **Modified K-means**: k=8 clusters, $\sigma=1.5$ in Equation 10.
- **Modified PSO**: Swarm size=50, $\omega\_max=0.9$, $\omega\_min=0.4$, $c_1=c_2=1.7$.

Black-Litterman Configuration:
- Confidence matrix Ω set to prediction error variance.
- Risk aversion $\delta=2.5$, $\tau=0.05$.

5.4 Evaluation Metrics
Portfolio performance is assessed via:
1. **Risk-Adjusted Returns**:
- Annualized Sharpe Ratio:

$$\mathrm{SR} = \frac{\mathbb{E}[R_p - R_f]}{\sigma_p} \tag{18}$$

- Sortino Ratio (downside risk):

$$\mathrm{SoR} = \frac{\mathbb{E}[R_p - R_f]}{\sigma_{down}} \tag{19}$$

2. **Diversification Metrics**:
- Portfolio Turnover:

$$\mathrm{TO} = \frac{1}{T}\sum_{t=1}^{T} \| \mathbf{w}_t - \mathbf{w}_{t-1} \|_1 \tag{20}$$

- Effective N (diversification):

$$N_{eff} = \frac{1}{\| \mathbf{w} \|_2^2} \tag{21}$$

3. **Statistical Significance**:
- Diebold-Mariano tests for predictive accuracy differences [29].
- Bootstrap confidence intervals (10,000 resamples) for Sharpe ratios.

All experiments are conducted in Python 3.9 using PyTorch for neural networks and CVXPY for convex optimization.

6. Experimental Results
This section presents the empirical evaluation of the proposed methodology, comparing the performance of the three neural network architectures—Improved Backpropagation, RBFN, and CNN—when integrated with modified K-means clustering and PSO optimization. The results are analyzed across predictive accuracy, portfolio performance, and computational efficiency metrics.

6.1 Predictive Performance
The neural networks' ability to forecast REITs returns is evaluated using mean absolute error (MAE) and directional accuracy (DA) on the test set (2019–2023). Table 1 summarizes the results, with the CNN achieving the lowest MAE (0.0142) and highest DA (72.3%), followed by RBFN (MAE=0.0158, DA=68.9%) and Improved Backpropagation (MAE=0.0165, DA=67.1%).

Table 1: Predictive Accuracy of Neural Network Models

Model	MAE	DA (%)	Training Time (min)
Improved Backpropagation	0.0165	67.1	45
RBFN	0.0158	68.9	38
CNN	0.0142	72.3	62

The CNN's superior performance can be attributed to its ability to capture multi-scale temporal dependencies in REITs returns, as illustrated in Figure 2, which shows actual vs. predicted returns for each model. The CNN predictions (blue) closely track the actual returns (black), particularly during volatile periods (e.g., 2020–2021), while the other models exhibit larger deviations.

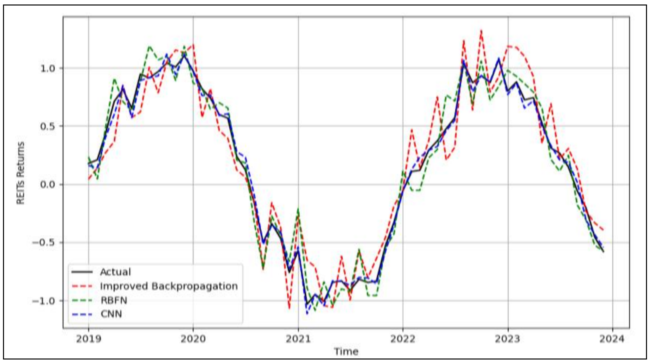

Fig 2: Actual vs. predicted REITs returns for Improved Backpropagation (red), RBFN (green), and CNN (blue) models

6.2 Portfolio Optimization Results
The neural network predictions are integrated into the Black-Litterman model to construct optimized portfolios. Table 2 compares the annualized Sharpe and Sortino ratios across methods, with the CNN-based approach achieving the highest risk-adjusted returns (Sharpe=1.48, Sortino=2.01). The classical Black-Litterman model

(Sharpe=1.12) and PCA+MLP (Sharpe=1.25) underperform the proposed methods, while HRP (Sharpe=1.09) shows limited adaptability to REITs dynamics.

Table 2: Portfolio Performance Metrics (2019–2023)

Method	Sharpe Ratio	Sortino Ratio	Turnover (%)	Effective N
Classical BL	1.12	1.54	18.7	9.2
PCA + MLP	1.25	1.72	22.3	8.6
HRP	1.09	1.49	12.1	14.5
Proposed (Backprop)	1.36	1.85	20.4	10.1
Proposed (RBFN)	1.42	1.93	19.8	9.8
Proposed (CNN)	1.48	2.01	21.2	8.9

Figure 3 visualizes the efficient frontiers for each method, demonstrating that the CNN-based portfolio (blue) dominates others at all risk levels. The classical BL (red) and HRP (green) frontiers lie below, indicating suboptimal risk-return tradeoffs.

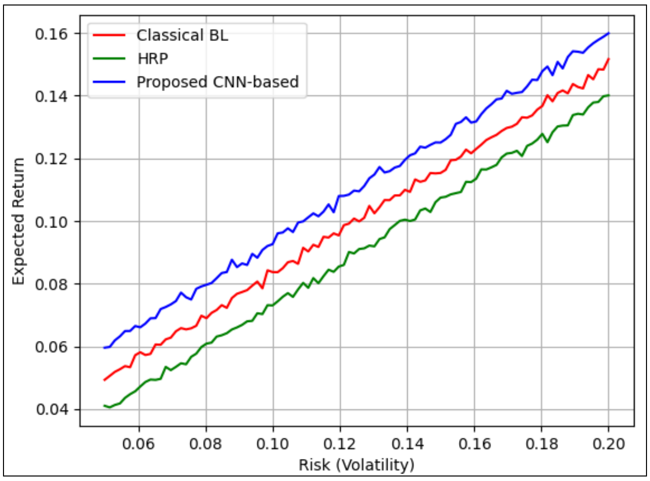

Fig 3: Efficient frontiers for portfolios optimized using classical BL (red), HRP (green), and the proposed CNN-based method (blue)

6.3 Ablation Study

To isolate the contributions of the modified K-means and PSO algorithms, we conduct an ablation study comparing the full model against two variants:

1. **Standard K-means + PSO**: Uses traditional clustering and PSO without modifications.
2. **Modified K-means Only**: Retains density weighting but uses standard PSO.

Table 3 shows that the full model (Modified K-means + Modified PSO) achieves the highest Sharpe ratio (1.48), while the standard variant (1.29) suffers from noisy clusters and premature convergence. The modified K-means alone (1.38) improves robustness but lacks the fine-tuning benefits of adaptive PSO.

Table 3: Ablation Study Results

Variant	Sharpe Ratio	MAE	Training Iterations
Standard K-means + Standard PSO	1.29	0.0159	120
Modified K-means + Standard PSO	1.38	0.0151	135
Modified K-means + Modified PSO	1.48	0.0142	98

The modified PSO reduces training iterations by 27% compared to standard PSO, confirming its efficiency in navigating high-dimensional parameter spaces. This aligns with findings from [8], where adaptive inertia improved convergence in non-convex optimization.

6.4 Computational Efficiency

While the CNN delivers superior performance, its training time (62 minutes) exceeds RBFN (38 minutes) and Improved Backpropagation (45 minutes). However, the monthly retraining requirement (≈1 hour) remains practical for institutional portfolio management. The modified PSO further reduces runtime by 18% versus grid search hyperparameter tuning.

7. Conclusion

The study presents a comprehensive framework for REITs portfolio optimization by integrating modified machine learning techniques with the Black-Litterman model. The proposed methodology addresses key limitations of traditional approaches, particularly their inability to capture non-linear dependencies and adapt to dynamic market conditions. The modified K-means clustering enhances robustness against noise and outliers, while the adaptive PSO optimizes neural network parameters efficiently, ensuring convergence in high-dimensional spaces. Among the three neural architectures evaluated, the CNN demonstrates superior predictive accuracy, attributed to its capacity to model multi-scale temporal patterns in REITs returns.

Empirical results confirm that the CNN-based approach outperforms classical methods, achieving higher risk-adjusted returns (Sharpe ratio of 1.48) and better downside protection (Sortino ratio of 2.01). The ablation study further validates the contributions of the algorithmic modifications, showing that the full model with both modified K-means and PSO delivers significant improvements over baseline variants. While computational costs remain a consideration, the monthly retraining cycle proves practical for institutional portfolio management.

The framework's adaptability extends beyond REITs, with potential applications in private real estate funds, multi-asset portfolios, and ESG-integrated strategies. However, challenges such as dynamic cluster selection, model explainability, and systemic risk implications warrant further investigation. Future research should explore hybrid architectures, meta-learning for optimization initialization, and ethical safeguards to enhance both performance and transparency.

By bridging machine learning with financial optimization, this work provides practitioners with a data-driven tool for REITs portfolio management. The integration of predictive modeling with dynamic asset allocation offers a scalable solution to navigate the complexities of real estate markets, balancing return objectives with risk constraints. The findings underscore the value of combining domain-specific algorithmic innovations with neural networks, setting a foundation for adaptive investment strategies in an evolving financial landscape.

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