

Deep Learning versus Classical Machine Learning in Portfolio Optimization with Downside Risk: Evidence from the Abu Dhabi Securities Exchange (ADX)

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Abstract: This study aimed to develop and evaluate a hybrid portfolio optimization framework integrating deep learning-based stock-return forecasting with Mean Semi-Absolute Deviation (MSAD) optimization to improve risk-adjusted asset allocation in the Abu Dhabi Securities Exchange. An applied quantitative design was employed using daily Open, High, Low, Close, and trading-volume data for 25 active ADX stocks. Three deep learning architectures—Deep Multilayer Perceptron (DMLP), one-dimensional Convolutional Neural Network (1D-CNN), and Long Short-Term Memory (LSTM)—were compared with Support Vector Regression (SVR). Predictors were constructed from rolling 20-day windows, and the dataset was partitioned into training, validation, and out-of-sample testing subsets. Forecasts were incorporated into an MSAD linear optimization framework, and stocks were ranked into five quintile portfolios. Predictive performance was assessed using MAE, MSE, and directional Hit Rates, while portfolio performance was evaluated through daily return and return-to-risk ratios. DMLP produced the lowest forecasting errors, with MAE=0.0163 and MSE=0.0013, and achieved the highest positive directional accuracy (HR+=0.5163). In portfolio optimization, DMLP+MSAD generated the strongest results for aggressive portfolios, producing daily returns of 0.1817 and 0.2164 and return-to-risk ratios of 0.49 and 0.78 for P1 and P3, respectively. SVR+MSAD showed greater stability in the defensive P2 portfolio, whereas CNN+MSAD demonstrated comparative resilience in negatively performing portfolios. Across the quintiles, MSAD-optimized AI strategies consistently exhibited superior risk-adjusted performance relative to equal-weighted allocation. Integrating predictive artificial intelligence models with downside-risk-based MSAD optimization improves portfolio construction under asymmetric and volatile market conditions. DMLP+MSAD is particularly effective for high-return strategies, whereas SVR and CNN may offer advantages under more defensive or adverse market regimes, indicating that optimal model selection should reflect investors' risk-return preferences.

Keywords: Deep Learning; Portfolio Optimization; Mean Semi-Absolute Deviation; Downside Risk; DMLP; Support Vector Regression; Abu Dhabi Securities Exchange.

1. Introduction

Portfolio optimization remains one of the central problems in financial decision-making because investors must continuously determine how limited capital should be distributed among competing assets while balancing expected return against exposure to risk. This problem has become more difficult as contemporary financial markets have grown increasingly dynamic, information-intensive, interconnected, and sensitive to abrupt

economic and geopolitical shocks. Asset prices now respond rapidly to heterogeneous information flows, behavioral reactions, changes in liquidity, and algorithmic trading activity, producing return processes characterized by non-linearity, temporal instability, asymmetric volatility, and extreme observations. Under these conditions, portfolio construction can no longer be treated solely as a static allocation problem based on historical averages; rather, it increasingly requires an integrated framework in which future return patterns are predicted and then translated into allocation decisions through an explicit risk-management mechanism. Recent quantitative portfolio research therefore emphasizes more adaptive methods capable of functioning under substantial uncertainty and changing market regimes [1], while multiscale and signal-oriented approaches further demonstrate the importance of extracting information embedded in complex financial dynamics before optimization is performed [2].

Traditional portfolio theory established the foundational principle that diversification should be guided by a formal trade-off between expected return and risk. Nevertheless, conventional variance-based approaches possess important limitations when applied to real financial markets. Variance treats favorable and unfavorable deviations from the expected return symmetrically, even though investors generally attach considerably greater economic importance to losses than to unexpected positive returns. In addition, return distributions frequently depart from normality and exhibit skewness, excess kurtosis, structural breaks, and fat tails, particularly in emerging and relatively volatile markets. These characteristics have encouraged the development of portfolio models that incorporate higher-order distributional properties [3] and alternative downside-oriented risk measures that more directly reflect unfavorable outcomes [4]. More recent portfolio research has similarly emphasized tail-sensitive optimization frameworks designed to represent the asymmetry of investment losses more realistically [5]. Consequently, the conceptual focus of portfolio risk management has gradually shifted from general volatility toward the magnitude and probability of adverse deviations.

One important development within this broader transition is the use of downside-risk optimization models such as Mean Semi-Absolute Deviation (MSAD). In contrast to variance-based optimization, MSAD concentrates on undesirable deviations below a target or reference return and therefore corresponds more closely to the practical risk concerns of investors. Because semi-absolute deviation can also be formulated within a linear optimization structure, it provides computational advantages when portfolio decisions involve multiple assets and constraints. Downside-oriented optimization is especially relevant in markets where return distributions are asymmetric and where large negative movements can have a disproportionate influence on realized portfolio performance. Empirical and methodological advances in portfolio analysis increasingly support the use of optimization frameworks that are more sensitive to undesirable return realizations rather than treating all volatility as equally harmful [4, 5]. In a directly relevant application, the combination of convolutional neural network forecasting with an MSAD portfolio model has demonstrated the feasibility of linking artificial-intelligence-based forecasts to downside-risk optimization in stock-market settings [6]. Such developments suggest that improvements in portfolio construction may depend not only on how risk is measured but also on the quality of the expected-return estimates supplied to the optimization model.

This issue is particularly important because traditional optimization models often use historical mean returns as proxies for future expected returns. Such estimates may be convenient, but they can be inadequate when the investment horizon is short or when recent market dynamics differ substantially from long-run historical conditions. Financial time series contain complex relationships that may evolve over time, and averaging past returns can suppress transient information that is potentially relevant to future price movements. Accordingly,

prediction-based portfolio optimization has emerged as a major research direction in which machine learning or deep learning models first forecast future asset behavior and those forecasts are subsequently used to construct portfolios. Research on prediction-based optimization using deep neural networks has demonstrated that predictive information can materially affect portfolio formation and asset-allocation outcomes [7]. Similarly, deep-learning-based preselection can improve the process through which candidate assets are identified before portfolio weights are determined [8]. Threshold-based portfolio approaches also show that the mechanism through which predicted information is translated into investment decisions is itself important for final portfolio performance [9].

The growing use of artificial intelligence in portfolio management reflects broader developments in financial time-series forecasting. Machine learning methods are capable of learning relationships from data without requiring the rigid functional assumptions typically imposed by conventional linear models. Among classical machine learning techniques, Support Vector Regression (SVR) has received considerable attention because of its ability to approximate non-linear functions, tolerate noisy observations, and achieve strong generalization through structural risk minimization. Its kernel-based formulation enables non-linear input patterns to be represented within a higher-dimensional feature space, making SVR a useful benchmark when complex financial relationships cannot be modeled effectively through standard regression. The mathematical relationship between support vector methods and non-linear optimization provides a strong foundation for their application to complex predictive problems [10], while continuing methodological development of support vector machines illustrates the adaptability of the broader SVM framework [11]. Moreover, research on SVR hyperparameter optimization demonstrates that model performance can be highly sensitive to the selection of parameters and optimization procedures, reinforcing the need for careful model calibration [12].

SVR and related machine learning approaches have also been applied directly to investment decision-making. The integration of machine learning with portfolio selection has been shown to support systematic financial trading and allocation decisions [13]. Similarly, portfolio-selection research combining multiclass support vector machines with genetic algorithms illustrates how predictive classification can be integrated with optimization procedures to improve stock selection [14]. Comparative applications of machine learning in portfolio construction further indicate that intelligent methods can contribute not only to forecasting but also to the identification and weighting of securities within an optimal portfolio [15]. Nevertheless, classical machine learning models may become constrained when financial data contain highly complex temporal interactions, multiple levels of non-linearity, and sequential dependencies extending across different time horizons. These limitations have contributed to the rapid adoption of deep learning in financial forecasting.

Deep learning extends conventional machine learning through multilayer architectures capable of automatically learning hierarchical representations from complex data. Rather than relying exclusively on manually engineered features, deep neural networks can transform raw or minimally processed inputs through successive non-linear layers, enabling the detection of patterns that may be difficult to specify a priori [16]. Systematic reviews of financial forecasting research have documented a substantial expansion in the use of deep learning for stock prices, returns, indices, and related financial variables [17], and subsequent reviews confirm that deep learning architectures continue to play an increasingly important role in financial time-series analysis [18]. Their relevance arises from the capacity to accommodate non-linearity, high-dimensional information, temporal dependencies, and interactions among market variables that are difficult to represent using conventional econometric structures.

Several deep learning architectures are especially relevant to financial forecasting. Deep Multilayer Perceptrons (DMLPs) use multiple fully connected hidden layers to approximate complex non-linear mappings between

predictor variables and outputs. Although their architecture is comparatively straightforward, multilayer perceptrons can achieve substantial predictive flexibility when appropriately trained. Research demonstrating the effectiveness of advanced DMLP structures in complex classification settings provides methodological evidence of the capacity of multilayer architectures to learn difficult non-linear patterns [19]. Within financial applications, deep learning models have likewise been used successfully to predict stock-market behavior, indicating that multilayer architectures can extract useful information from noisy price data [20]. Studies of artificial-intelligence-based stock prediction have further demonstrated the potential of such models to capture patterns that conventional statistical methods may overlook [21].

Long Short-Term Memory (LSTM) networks provide a different architectural advantage by explicitly modeling sequential dependence. Their gated memory structure was designed to mitigate the vanishing-gradient problem found in conventional recurrent networks, allowing information to persist across longer sequences. This property makes LSTM particularly attractive for financial data, where current returns may reflect patterns distributed across previous observations. Evidence from financial-market prediction has shown that LSTM networks can outperform memoryless approaches when temporal dependencies are economically meaningful [22]. More recent research continues to demonstrate the applicability of LSTM models to stock-price prediction and financial-market forecasting [23], while comprehensive analyses of LSTM techniques emphasize their flexibility across different market datasets, input structures, and forecasting horizons [24]. LSTM-based methods have also been applied to specialized financial markets, including futures forecasting, confirming their capacity to learn temporal structures in volatile price processes [25].

Importantly, LSTM forecasting has progressed beyond purely statistical prediction toward explicit portfolio construction. Quantitative trading research integrating LSTM-based stock prediction with portfolio optimization has shown that forecasts can be incorporated directly into allocation frameworks rather than evaluated only through prediction errors [26]. Similarly, an equity-market-neutral strategy constructed using LSTM-based stock prediction and selection demonstrates how sequential forecasting can support systematic asset screening and portfolio formation [27]. Hybrid deep-learning and volatility-modeling frameworks have also been developed for predicting aggregate stock-market returns, demonstrating the potential benefits of combining neural learning with established financial modeling techniques [28]. Collectively, these studies reinforce the view that the economic usefulness of deep learning depends on whether predictive outputs contribute meaningfully to subsequent investment decisions.

Convolutional Neural Networks (CNNs) provide another important approach. Although originally developed primarily for spatial data, one-dimensional CNNs have become increasingly useful for financial time series because convolutional filters can identify localized patterns, short-term motifs, and structural features within sequential market observations. CNN-based models can therefore extract relevant short-run configurations while reducing the influence of irrelevant noise. Studies applying CNN architectures to stock-price forecasting have reported their usefulness in identifying complex patterns in market data [29]. Comparative analyses of CNN and LSTM architectures further demonstrate that these models capture different aspects of temporal information, with CNNs emphasizing local structural features and LSTMs emphasizing sequential memory [30]. The use of CNN forecasting directly within an MSAD optimization model represents an especially important development because it demonstrates how local feature extraction can be connected to a downside-risk allocation objective [6].

Despite the rapid development of these methods, an important methodological problem remains. High predictive accuracy does not automatically imply high investment value. A model can achieve low statistical

forecast error yet still produce poor portfolio allocations if its errors occur at economically important moments or if the optimization mechanism amplifies prediction uncertainty. Conversely, a model with somewhat higher average prediction error may produce better portfolios if its forecasts more effectively discriminate between attractive and unattractive securities. This distinction has increasingly motivated researchers to evaluate forecasting models through decision-oriented criteria rather than relying only on measures such as mean squared error or mean absolute error. Out-of-sample forecast errors are particularly important because optimization procedures can translate even modest prediction errors into substantial changes in portfolio weights [31]. Thus, predictive performance and portfolio performance should be analyzed jointly rather than as independent stages.

This issue also highlights the importance of comparing architectures rather than assuming that deeper or more complex models will universally outperform classical alternatives. Different models capture different dimensions of financial information, and their relative usefulness may depend on the market regime, return distribution, feature set, forecasting horizon, and investor objective. Research comparing deep learning and other intelligent methods suggests that architecture-specific advantages can vary substantially across financial applications [17, 18]. Moreover, recent evaluations of quantitative portfolio management under market uncertainty emphasize that no single technique eliminates the need to align model selection, risk measurement, and investment objectives [1]. Consequently, the relevant empirical question is not merely whether deep learning improves forecasting, but whether particular architectures generate superior economic outcomes when embedded within a portfolio optimization framework.

The Abu Dhabi Securities Exchange (ADX) provides an appropriate setting for examining this question. As an emerging capital market exposed to changing liquidity conditions, sectoral concentration, global financial developments, energy-market dynamics, and regional economic transformations, the ADX presents a demanding environment for both return forecasting and risk management. In such a setting, reliance on symmetric volatility measures or static historical averages may inadequately represent the investment problem. Prediction-based allocation combined with a downside-focused risk measure offers a potentially more responsive alternative. At the same time, model comparison is essential because the relative performance of DMLP, CNN, LSTM, and SVR may vary across assets and portfolio risk profiles. Existing studies establish the usefulness of deep learning for market forecasting [22, 23], intelligent methods for portfolio construction [7, 8, 13], and downside-sensitive optimization [4, 6], but the direct comparison of multiple deep architectures and a classical SVR benchmark within a unified MSAD framework remains comparatively underexplored, particularly in the ADX context.

A further contribution lies in evaluating model performance across differentiated portfolio segments rather than reporting only an aggregate optimized portfolio. Ranking securities according to predicted returns and organizing them into portfolios representing different expected-return profiles provides an opportunity to determine whether the economic utility of a predictive architecture changes across aggressive, intermediate, and defensive investment settings. This approach is consistent with the broader understanding that asset selection, prediction, optimization, and investor objectives should be treated as interconnected elements of the portfolio problem [9, 26]. It also permits a more informative assessment of whether sophisticated predictive models genuinely distinguish high-potential securities from lower-performing assets and whether such discrimination translates into improved return-to-downside-risk performance.

Accordingly, the present study addresses the intersection of three closely related gaps: the inadequacy of symmetric risk measures for investors primarily concerned with losses, the limitations of historical expected-return estimates in dynamic markets, and the insufficient connection between forecasting accuracy and realized portfolio

efficiency. By integrating AI-generated expected returns with MSAD optimization, the proposed framework links the predictive layer directly to the risk-management and allocation layer. Comparing DMLP, 1D-CNN, and LSTM against SVR further permits assessment of whether increasingly sophisticated deep architectures deliver economically meaningful improvements over a robust classical machine-learning benchmark, while comparison with equal-weighted allocation provides a practical baseline for evaluating the incremental value of optimization.

Therefore, this study aims to develop and comparatively evaluate DMLP-, CNN-, LSTM-, and SVR-based return-forecasting models integrated with Mean Semi-Absolute Deviation optimization to determine their predictive and risk-adjusted portfolio performance across different investment profiles in the Abu Dhabi Securities Exchange.

2. Methods and Materials

This research follows an applied study design, employing a quantitative and operational approach aimed at enhancing the precision of stock return forecasting and optimizing portfolio allocation. The applied nature of this study is underscored by the direct implementability of its findings within financial decision-making environments, providing a robust mechanism for investors to significantly augment portfolio performance.

The proposed framework follows a two-stage, decision-centric methodology. In the first stage, state-of-the-art artificial intelligence algorithms are deployed to identify and forecast the non-linear patterns and dynamic trends inherent in financial time series. In the second stage, these forecasts are integrated into a Mean Semi-Absolute Deviation (MSAD) mathematical optimization framework. Distinct from traditional approaches that rely on historical averages, this framework explicitly treats model forecast errors as the primary proxy for downside risk. By utilizing the forecasting models to capture market dynamics and the MSAD model to penalize downside risk, this systematic approach establishes an organic nexus between the intelligent forecasting layer and the financial decision-making layer, providing a comprehensive framework to navigate the complex stochasticity of capital markets.

The raw dataset, comprising daily Open, High, Low, and Close (OHLC) prices, along with trading volume, was extracted from verified financial databases (ADX and Investing.com). To ensure temporal integrity and data consistency, all datasets were meticulously synchronized to account for official market holidays and non-trading days in the ADX, thereby maintaining a continuous time-series structure without temporal gaps. Following the methodology proposed by Ma and Wang (2020), the input for each predictive model is structured based on the daily growth rates of these features across a rolling 20-day temporal window. Consequently, each input vector, with dimensions of 5×20 (totaling 100 features), is fed into the deep learning models to facilitate the learning of complex temporal dependencies within the financial time series. The rolling window approach employs a sliding technique with a stride of 1, ensuring a continuous capture of temporal dynamics throughout the dataset.

To ensure the integrity and convergence of the neural network architectures, the following pre-processing protocols were implemented:

- **Outlier Detection and Treatment:** Anomalous fluctuations resulting from exogenous market shocks were identified and treated based on daily return distributions. This procedure is critical to mitigate the adverse effects of extreme values on the model's objective function and to prevent biased parameter estimation.
- **Feature Normalization:** Data were standardized using the mean (μ) and standard deviation (σ), transforming input features into a Z-score format. This normalization is essential to stabilize the optimization process, facilitate optimal convergence of the neural network layers, and ensure balanced gradient descent updates.

- **Temporal Data Partitioning:** The dataset was partitioned into three distinct subsets: **Training** (to fit patterns and calibrate network weights), **Validation** (to fine-tune hyperparameters and prevent overfitting), and **Out-of-Sample Testing** (to evaluate the model's final predictive performance and generalization capabilities on unseen data).

To capture the multifaceted dynamics of financial time series, this study employs a hybrid suite of predictive models, ranging from foundational machine learning algorithms to advanced deep learning architectures.

- **Long Short-Term Memory (LSTM) Networks:** To address the vanishing gradient problem inherent in standard Recurrent Neural Networks (RNNs), we deploy an LSTM architecture equipped with specialized gating mechanisms—the input, forget, and output gates. The model maintains long-term dependencies through the cell state (c_t), which acts as an internal memory mechanism. This structure is particularly adept at modeling non-stationary market dynamics and capturing persistent temporal patterns that influence future stock returns (Song et al, 2024).
- **One-Dimensional Convolutional Neural Networks (1D-CNN):** While LSTMs are tailored for temporal sequences, 1D-CNNs are utilized here to identify local feature hierarchies. By employing learnable convolutional filters and max-pooling layers, the 1D-CNN effectively extracts critical trading motifs and structural patterns from input vectors. This feature extraction capability allows the model to compress high-frequency noise and highlight latent momentum signals within the 20-day rolling window.
- **Deep Multilayer Perceptron (DMLP):** Serving as a foundational neural architecture, the DMLP consists of multiple dense, fully connected layers. We utilize the Rectified Linear Unit (ReLU) activation function to mitigate non-linear saturation, allowing the model to map intricate, non-linear relationships between historical inputs and expected future returns. This architecture serves as a baseline for evaluating the marginal value added by more complex sequential or spatial modeling structures.

As the classical baseline model, Support Vector Regression (SVR) is implemented with a Radial Basis Function (RBF) kernel to map input data into a high-dimensional feature space. Unlike traditional regression methods that minimize empirical risk, SVR is predicated on the Structural Risk Minimization (SRM) principle, which enhances generalization performance. By defining an ϵ -insensitive tube, the SVR objective function disregards residuals within a pre-defined threshold, focusing exclusively on the support vectors that determine the optimal regression hyperplane. This robust formulation makes SVR highly resilient to the structural noise and volatility characteristic of the ADX, providing a stable benchmark against which the predictive performance of deep learning architectures is evaluated (Yeh et al, 2021).

All predictive models were optimized using the Adam algorithm, with the Mean Absolute Error (MAE) utilized as the objective loss function to ensure robustness against outliers. To mitigate the risk of overfitting, an Early Stopping criterion was implemented with a patience parameter set to 10 epochs. The optimal hyperparameters for each architecture—including learning rates, batch sizes, and architectural configurations—were determined through an extensive empirical grid search. The specific configurations are summarized in Table 1.

Table 1: Hyperparameter Specifications for Predictive Models

Model	Hyperparameter	Value / Configuration
DMLP	Hidden Layers / Nodes	2 Layers / [32, 64]
	Optimizer / Loss	Adam / MAE
	Learning Rate / Batch Size	0.01 / 32

	Activation / Patience	ReLU / 10
1D-CNN	Conv. / Max-pooling Layers	1 Layer / 1 Layer (pool_size=2)
	FC Layers / Nodes	2 Layers / [32, 64]
	Filter Numbers	64
	Optimizer / Activation	Adam / ReLU
	Batch Size / Patience	32 / 10
LSTM	Hidden Layers / Nodes	2 Layers / 50
	Dropout / Recurrent Dropout	0.2 / 0.2
	Learning Rate / Batch Size	0.01 / 32
	Optimizer / Patience	Adam / 10
SVR	C / gamma	100 / 0.1
	Epsilon	0.1

This section delineates the integration of AI-driven return forecasts into the Mean Semi-Absolute Deviation (MSAD) optimization framework. In contrast to the classical Markowitz Mean-Variance framework, which treats upside and downside deviations symmetrically, the MSAD model focuses exclusively on downside risk. By doing so, it offers a more nuanced and robust risk-management mechanism, particularly for investors operating in asymmetric market environments where tail risk is a primary concern.

Following the predictive modeling stage (utilizing LSTM, CNN, DMLP, and SVR), we derive the projected returns ($\hat{R}_{it}$) for each asset i at time t . The predictive error (ϵ_{it}), which serves as a proxy for forecasting uncertainty and model-based risk, is defined as:

$$\epsilon_{it} = R_{it} - \hat{R}_{it}$$

where R_{it} and $\hat{R}_{it}$ represents the realized and forecasted returns, respectively. These residual terms establish the empirical foundation for assessing downside risk, directly informing the input series required for the MSAD optimization objective.

To evaluate the performance of our predictive strategies across diverse risk-return profiles, the 25 selected stocks are ranked by their expected returns and partitioned into five distinct quintile portfolios, each comprising five assets:

- **Portfolio 1 (Aggressive):** Comprising the top five assets with the highest projected returns.
- **Portfolios 2–4 (Intermediate):** Representing a spectrum of moderate risk-return profiles.
- **Portfolio 5 (Conservative):** Comprising the five assets with the lowest projected returns.

This stratification enables a granular performance assessment of the proposed strategies, facilitating a comprehensive understanding of how model-based return forecasts translate into optimized asset allocation under varying investment horizons.

The optimal asset weights (w_i) are derived by minimizing the downside deviation of portfolio returns relative to a pre-defined target threshold. The optimization problem is formulated as follows:

Objective Function:

$$\min_w \frac{1}{T} \sum_{t=1}^T d_t$$

Subject to:

1. **Downside Risk:** $d_t \geq \sum_{i=1}^n w_i (R_{it} - \hat{R}_{it})$ and $d_t \geq 0$
2. **Target Return:** $\sum_{i=1}^n w_i E(R_i) \geq \rho$
3. **Budget Constraint:** $\sum_{i=1}^n w_i = 1$
4. **No-Short Selling Constraint:** $w_i \geq 0$

In this formulation, the auxiliary variable d_t is constrained by $d_t \geq Target - R_p$ and $d_t \geq 0$ which effectively linearizes the semi-absolute deviation objective.

In this context, d_t denotes an auxiliary variable that captures negative deviations from the target return. Due to this linear structure, the MSAD framework presents a significant computational advantage over variance-based models. Specifically, it circumvents the complex matrix inversions associated with quadratic programming (QP) solvers, thereby ensuring rapid convergence and operational stability—a critical feature for high-dimensional portfolio construction in complex capital markets.

To rigorously assess the performance of the proposed framework, evaluation is conducted at two distinct tiers: predictive accuracy for the forecasting models and economic performance for the optimized asset allocation strategies. This dual-level evaluation ensures that both the statistical validity of the forecasts and the practical efficiency of the portfolio construction are comprehensively analyzed.

To quantify the deviation between the forecasted returns $\hat{R}_{it}$ and realized returns R_{it} over the forecast horizon (T), the following statistical loss functions are employed:

Mean Squared Error (MSE): By squaring the prediction errors, this metric penalizes large deviations disproportionately, thereby highlighting the model's susceptibility to extreme outliers:

$$MSE = \frac{1}{T} \sum_{t=1}^T (\hat{R}_{it} - R_{it})^2$$

Mean Absolute Error (MAE): This metric reports the average absolute deviation without regard to the direction of error, providing a linear, balanced assessment of prediction accuracy:

$$MAE = \frac{1}{T} \sum_{t=1}^T |\hat{R}_{it} - R_{it}|$$

Hit Rate (HR): This directional accuracy metric measures the frequency with which the model correctly predicts the sign of price movements (HR⁺ for upward and HR⁻ for downward trends).

Following the construction of the five quintile portfolios via the MSAD optimization framework, the economic efficiency of the resulting strategies is analyzed using the following metrics:

Expected Portfolio Return (E(R_p)): The weighted average return of the assets within the portfolio over the testing period, representing the baseline profitability of the allocation strategy.

Portfolio Semi-Absolute Deviation (SAD): Unlike traditional variance—which penalizes both upside and downside volatility symmetrically—this metric isolates downside risk by exclusively considering deviations below the target threshold. This serves as a more accurate proxy for an investor's true exposure to risk:

$$SAD(X) = \frac{1}{T} \sum_{t=1}^T \left| \sum_{i=1}^n w_i R_{it} - Target \right|$$

Reward-to-Risk Ratio: This efficiency metric quantifies the return generated per unit of downside risk. Higher values signify superior risk-adjusted performance, indicating that the portfolio allocation successfully maximizes returns relative to its exposure to tail risk:

$$Ratio = \frac{E(R_p)}{SAD(X)}$$

Finally, it is acknowledged that transaction costs were not explicitly incorporated in the current optimization framework; however, this provides a clean laboratory environment for evaluating the raw predictive efficacy of the intelligent models, leaving real-world friction integration for future research extensions.

3. Findings and Results

Following the training phase on historical data, the proposed models were implemented on an out-of-sample test dataset, specifically covering the 2023 fiscal year. To facilitate a rigorous and objective evaluation of predictive performance, the model outputs were subjected to a re-scaling procedure, mapping the forecasts back to their original market scale. This ensures a direct and consistent comparability against the realized return series from the Abu Dhabi Securities Exchange (ADX).

To ensure the robustness of our results, the dataset was partitioned into three distinct subsets: training (80%), validation (10%), and testing (10%). This segmentation is critical for optimizing model parameters, mitigating the risk of overfitting, and ensuring generalizability. An illustrative example of this partitioning scheme for the National Oil (ADNOCDIST) stock is presented in Figure 1.



Figure 1. Data partitioning scheme for training, validation, and testing periods (Example: ADNOCDIST).

Furthermore, Figure 2 illustrates the distribution of daily asset returns across the study period, providing insights into the market's volatility characteristics prior to evaluating the predictive performance of our models.

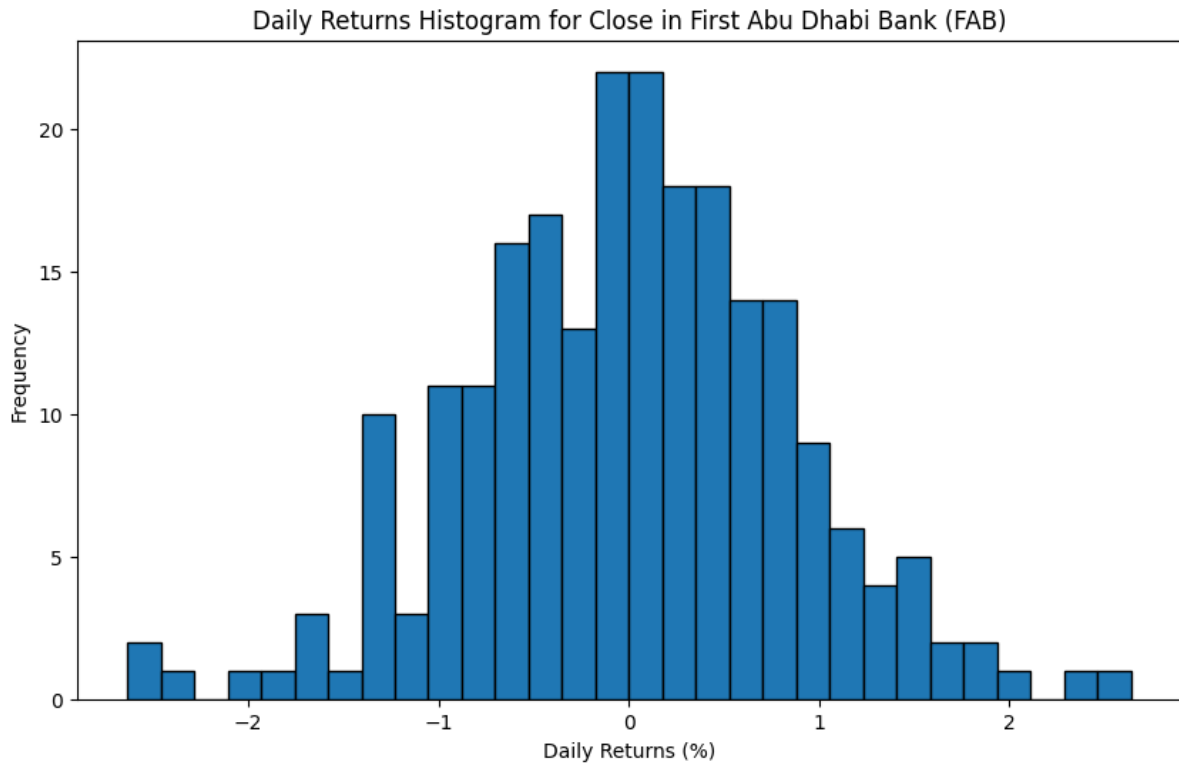


Figure 2. Distribution of daily asset returns

To rigorously evaluate the economic efficiency and predictive stability of the deep learning and machine learning models, we employ a multi-faceted set of statistical metrics. These include the Mean Squared Error (MSE), Mean Absolute Error (MAE), and overall directional Hit Rate (HR), alongside granular accuracy assessments for positive (HR⁺) and negative (HR⁻) market movements. The detailed statistical performance of the DMLP, LSTM, CNN, and SVR models for the 2023 fiscal year is summarized in Table 2.

Table 2. Predictive performance comparison of DMLP, LSTM, CNN, and SVR models for 2023

Model	Metric	MAE	MSE	H _R	H _R ⁺	H _R ⁻
DMLP	Mean	0.0163	0.0013	0.4760	0.5163	0.5499
	Standard Deviation	0.0119	0.0033	0.0645	0.0777	0.0490
LSTM	Mean	0.0263	0.0025	0.4762	0.4744	0.5816
	Standard Deviation	0.0260	0.0057	0.0724	0.1224	0.0930
CNN	Mean	0.0175	0.0015	0.4677	0.4827	0.5599
	Standard Deviation	0.0170	0.0043	0.0633	0.0857	0.0576
SVR	Mean	0.0678	0.1537	0.4456	0.4746	0.5475
	Standard Deviation	0.1336	0.2015	0.0603	0.1344	0.0906

An analysis of the results presented in Table 2 reveals that the Deep Multilayer Perceptron (DMLP) architecture exhibited superior predictive stability and accuracy throughout 2023 compared to the alternative models. Specifically, the DMLP achieved the lowest error metrics, with a Mean Absolute Error (MAE) of 0.0163 and a Mean Squared Error (MSE) of 0.0013. Furthermore, the volatility of these forecasting errors—measured by the standard deviation—was minimized under the DMLP configuration, underscoring the model's reliability in handling market stochasticity.

Regarding directional accuracy, the DMLP model yielded the highest average Hit Rate for positive price movements (HR^+) at 0.5163, while concurrently demonstrating the lowest standard deviation in this metric. Although the performance gaps in the overall HR and negative directional hit rate (HR^-) metrics were less pronounced, the consistent outperformance of the DMLP across both magnitude-based and directional loss functions led to its selection as the benchmark model for the subsequent asset allocation phase. These empirical results are consistent with existing literature, which frequently highlights the robustness of deep learning architectures in modeling non-linear financial time series.

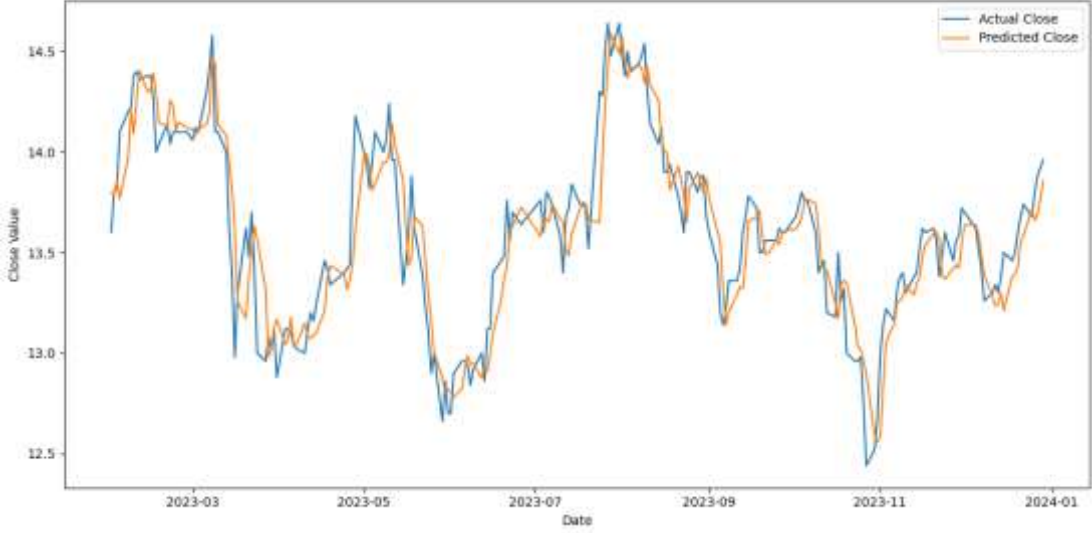


Figure 3. Forecasting performance of the trained DMLP model on test data

The observed variations in predictive performance can be attributed to the interplay between the input feature space and the underlying architectural designs of the employed models. Given that the input window is constrained to the 20-day historical look-back period ($time_steps = 20$), the informational density is insufficient to capture long-range temporal dependencies. Consequently, the LSTM network—which is fundamentally engineered to exploit long-term sequential memory—fails to fully manifest its theoretical advantages under such limited temporal constraints.

Similarly, the CNN architecture, which excels at extracting spatial patterns and complex structural features, faces bottlenecks due to the relatively narrow breadth of market input features. The limited feature space restricts the CNN from leveraging its intrinsic capabilities in hierarchical pattern recognition. These findings suggest that the predictive power of both LSTM and CNN frameworks could be significantly enhanced in future research by expanding the feature dimensionality and incorporating a more comprehensive historical look-back window, thereby allowing these architectures to better capture the latent dynamics of the market.

The second phase of the empirical research integrates the return forecasts derived from the AI models with a mathematical optimization framework. To this end, the asset allocation strategy is predicated on ranking the investment universe in descending order of their predicted annualized returns. For each model, all stocks listed on the Abu Dhabi Securities Exchange (ADX) were sorted based on their expected performance. Subsequently, the top 25 stocks were selected and partitioned into five distinct quintile portfolios, each comprising five unique assets. The first quintile portfolio (Q1) consists of the top-ranked stocks with the highest growth potential, while the fifth quintile portfolio (Q5) contains the assets with the lowest predicted returns within this top-tier selection.

Following the sorting process, the MSAD (Mean Semi-Absolute Deviation) linear programming model is applied to determine the optimal asset weights. We set a target daily portfolio return of $R_p = 0.15$, reflecting the risk appetite of investors in the volatile Abu Dhabi market. To benchmark the effectiveness of this downside-risk-focused optimization, we also construct an Equal-Weighted (EW) portfolio, which serves as a baseline for performance evaluation in the subsequent analysis.

In this phase, the Mean Semi-Absolute Deviation (MSAD) linear programming model is applied to the quintile portfolios (P1–P5) generated by the DMLP, CNN, LSTM, and SVR models. The objective is to minimize downside risk while achieving a target daily return of $R_p = 0.15\%$.

Before comparing the predictive architectures, we first evaluate the effectiveness of the MSAD optimization framework by benchmarking each AI-driven model against its corresponding Equal-Weighted (EW) strategy. The comparative analysis across all quintile portfolios reveals that the MSAD approach consistently yields superior risk-adjusted returns compared to passive EW allocation.

Having validated the MSAD framework, we now compare the performance of the four AI-based frameworks (DMLP+MSAD, CNN+MSAD, LSTM+MSAD, and SVR+MSAD) under the optimized MSAD regime. These comparative performance metrics are summarized in Table 3, while Figure 3 visualizes the risk-return efficiency for Portfolio 1 (P1).

Table 3. Comparative performance metrics of optimized portfolios by AI models

	Metric	DMLP+MSAD	CNN+MSAD	LSTM+MSAD	SVR+MSAD
P1	Daily Return	0.1817	0.1611	0.1042	0.1506
	Ret./Risk Ratio	0.49	0.31	0.25	0.23
P2	Daily Return	0.0029	0.028	0.0041	0.0292
	Ret./Risk Ratio	0	0.05	0.01	0.1
P3	Daily Return	0.2164	0.1248	0.0045	0.1207
	Ret./Risk Ratio	0.78	0.48	0.52	-0.121
P4	Daily Return	-0.2789	-0.2218	-0.1053	-0.0654
	Ret./Risk Ratio	-0.64	-2.13	-0.35	-0.13
P5	Daily Return	0.1333	-0.1646	-0.3103	-0.3631
	Ret./Risk Ratio	0.34	-0.28	-0.83	-145.2

Note: Ret./Risk Ratio refers to the Return-to-Risk Ratio.

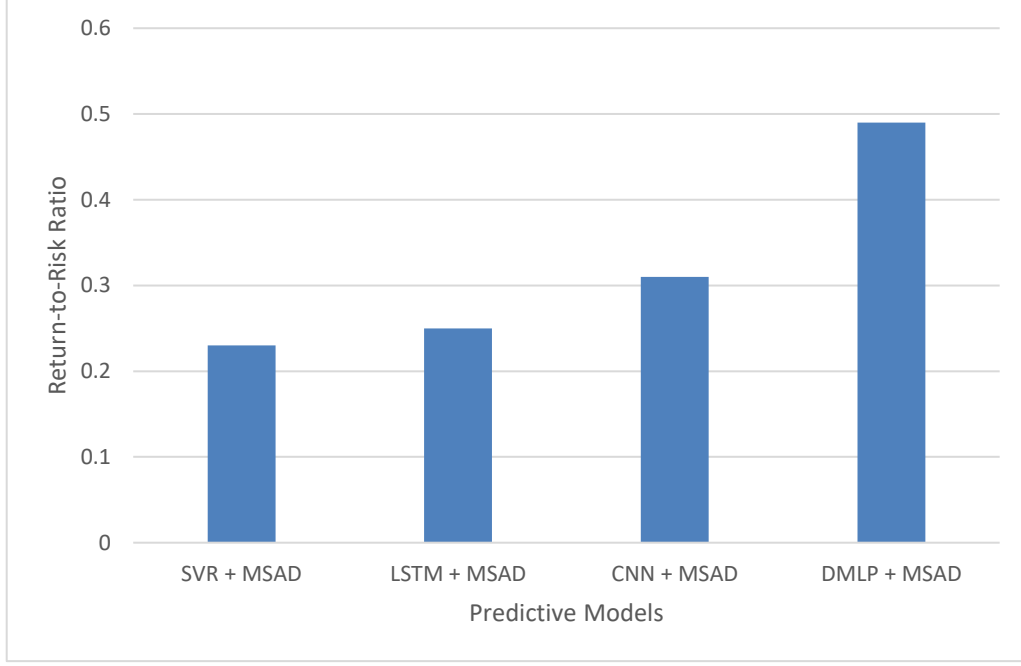


Figure 4. Comparison of return-to-risk efficiency across AI-based models for Portfolio 1 (P1).

The results reveal distinct performance patterns across the AI-based frameworks, suggesting that the effectiveness of each model is intrinsically linked to the target portfolio's risk profile. As evidenced by the results in Table 3 and Figure 4, the DMLP+MSAD configuration consistently delivers the most robust performance in high-growth portfolios (P1 and P3). The DMLP+MSAD model achieves a superior position on the efficiency frontier for P1, which unequivocally confirms its dominance in aggressive growth strategies.. This demonstrates the capacity of the DMLP architecture to capture complex non-linear market dependencies and translate them into highly efficient asset allocations. In contrast, the SVR+MSAD model exhibits superior stability in low-volatility or defensive scenarios (P2), maintaining a balanced risk-return profile. This stability aligns with SVR's principle of Structural Risk Minimization (SRM), which penalizes over-sensitivity to noise, making the model naturally suited for low-volatility asset regimes.

Furthermore, the performance gradient observed across the quintiles—ranging from significant positive returns in P1 and P3 to negative trajectories in P4 and P5—serves as a robust validation of our ranking strategy. Rather than representing model failure, the consistent negative returns in the P4 and P5 quintiles demonstrate the models' high precision in discriminating between high-potential assets and underperforming stocks. By accurately identifying these low-growth assets, the proposed framework empowers investors to effectively bypass potential 'value traps' within the ADX market, thereby enhancing overall portfolio resilience.

While specific performance variations exist, the overall findings suggest that the DMLP+MSAD model provides the highest economic utility for aggressive portfolio strategies, whereas the SVR and CNN frameworks offer potential advantages in specific defensive market conditions. Crucially, our comparative analysis against the Equal-Weighted (EW) benchmark demonstrates that the AI-integrated MSAD models consistently deliver superior risk-adjusted returns, effectively mitigating downside exposure relative to passive strategies.

4. Discussion and Conclusion

The present study examined whether integrating artificial-intelligence-based return forecasting with Mean Semi-Absolute Deviation (MSAD) optimization can improve portfolio construction in the Abu Dhabi Securities Exchange (ADX), while also determining whether different predictive architectures exhibit distinct advantages across portfolio risk profiles. The findings provide evidence that the economic usefulness of predictive models depends not only on their statistical accuracy but also on the manner in which their forecasts are incorporated into a downside-risk-sensitive optimization framework. At the forecasting stage, the Deep Multilayer Perceptron (DMLP) demonstrated the strongest overall predictive performance among the four examined models. It achieved the lowest Mean Absolute Error (MAE = 0.0163) and Mean Squared Error (MSE = 0.0013), while also showing comparatively low variability in forecast error. In directional terms, DMLP produced the highest positive-movement hit rate (HR+ = 0.5163). By comparison, LSTM recorded MAE = 0.0263 and MSE = 0.0025, CNN recorded MAE = 0.0175 and MSE = 0.0015, and SVR produced substantially larger errors, particularly MSE = 0.1537 and MAE = 0.0678. These results indicate that, within the specific input structure and 20-day rolling window used in this study, the DMLP architecture was better able to map the non-linear relationship between recent OHLCV information and subsequent returns.

The superior predictive performance of DMLP is broadly consistent with the proposition that multilayer neural architectures can identify complex non-linear mappings when appropriately structured and trained. Although the application domain differs, evidence concerning the capacity of discrete learning-based multilayer perceptron models to achieve robust classification performance supports the broader methodological usefulness of DMLP-type architectures for complex prediction problems [19]. In financial settings, prior studies have similarly shown that deep-learning approaches can extract latent information from noisy market data and improve stock-price and return forecasting [20, 21]. More generally, the growing literature on financial time-series forecasting identifies deep learning as particularly suitable for markets characterized by non-linearity, temporal instability, and high-dimensional information [17, 18]. The current findings therefore reinforce the view that deep architectures can provide useful predictive information in financial markets, but they also show that architectural complexity alone does not guarantee superior performance.

The weaker performance of LSTM relative to DMLP is particularly important. LSTM networks are specifically designed to capture long-range sequential dependencies, and previous evidence has documented their effectiveness in financial forecasting [22–24]. LSTM-based approaches have also generated encouraging results in portfolio construction and quantitative trading [26, 27], while applications to futures and stock-index forecasting have confirmed their ability to represent temporal dependencies in volatile financial series [25, 28]. Nevertheless, the present study used a 20-day look-back window, which may have limited the extent to which LSTM could exploit its principal architectural advantage. A relatively short sequence provides less opportunity for recurrent memory mechanisms to learn extended temporal dependencies. Consequently, the present finding does not contradict the broader LSTM literature; rather, it suggests that the performance of a forecasting architecture is conditional on the structure, temporal depth, and informational richness of the data supplied to it.

A comparable explanation applies to CNN performance. CNN achieved a relatively low MAE of 0.0175 and MSE of 0.0015, placing it close to DMLP in magnitude-based forecasting accuracy, but it did not consistently dominate the other models across all directional metrics. One-dimensional convolutional architectures are particularly effective at identifying local structures and short-term motifs within sequential data. Previous studies have

supported their usefulness in financial time-series prediction [29, 30], and CNN-based portfolio forecasting combined with MSAD has already demonstrated promising results in an equity-market setting [6]. In the present study, however, the feature space was limited primarily to rolling OHLCV growth-rate information. This may have constrained the CNN's capacity to learn richer hierarchical representations. Thus, the findings suggest that CNN may become more advantageous when the input space includes a broader collection of technical, fundamental, sentiment, or macroeconomic variables.

The results obtained for SVR also provide an important benchmark. SVR exhibited markedly larger average forecasting errors than the deep learning models, suggesting that the deep architectures were more effective in approximating the non-linear market dynamics present in the ADX data. This result is consistent with research showing that deep learning can outperform classical machine-learning methods in complex financial prediction environments [7, 8]. However, the results should not be interpreted as implying that SVR lacks value. SVR remains theoretically attractive because structural risk minimization and kernel-based transformation can provide strong generalization under noisy conditions [10, 11]. Moreover, SVR performance is sensitive to hyperparameter specification, and appropriate tuning can materially alter predictive performance [12]. Prior research has also shown that SVM-based models can contribute effectively to portfolio selection and trading decisions [13-15]. Importantly, the second-stage results of the current study confirm that a model with weaker aggregate forecasting accuracy can still provide economic value within particular portfolio regimes.

The portfolio optimization results provide the most important evidence in this regard. For the aggressive P1 portfolio, DMLP+MSAD generated the highest daily return of 0.1817 and the highest return-to-risk ratio of 0.49, compared with 0.1611 and 0.31 for CNN+MSAD, 0.1042 and 0.25 for LSTM+MSAD, and 0.1506 and 0.23 for SVR+MSAD. A similar pattern occurred in P3, where DMLP+MSAD achieved a daily return of 0.2164 and return-to-risk ratio of 0.78, outperforming CNN+MSAD, LSTM+MSAD, and SVR+MSAD. These findings indicate that DMLP forecasts were particularly useful when the optimization problem focused on stocks classified into higher expected-return segments. The result aligns with research showing that deep-neural-network forecasts can improve prediction-based portfolio optimization [7] and that deep learning can enhance stock preselection before portfolio formation [8]. Likewise, previous research integrating deep learning with portfolio optimization has demonstrated that predictive gains can translate into improved allocation decisions when forecasts are embedded directly in the investment process [26].

The performance of DMLP+MSAD in aggressive portfolios may be explained by the model's ability to capture dominant non-linear patterns among stocks exhibiting stronger predicted growth signals. When return opportunities are pronounced, a flexible multilayer architecture may distinguish more effectively between securities with genuinely strong patterns and those whose historical movements are largely noise. This interpretation is compatible with evidence that modern deep learning architectures can discover non-linear financial relationships that conventional models may fail to represent [17, 18]. It also supports the broader prediction-based optimization paradigm, in which the value of a forecast should ultimately be judged by the quality of the decision it produces rather than by prediction error alone [7]. The superior P1 and P3 outcomes therefore provide an economic validation of DMLP forecasts beyond their lower MAE and MSE values.

Nevertheless, the results also demonstrate that DMLP did not dominate every portfolio. In P2, SVR+MSAD produced the highest daily return of 0.0292 and the strongest return-to-risk ratio of 0.10, whereas DMLP+MSAD generated a daily return of only 0.0029 and a return-to-risk ratio close to zero. This finding is particularly relevant because it demonstrates that the model with the best average predictive accuracy is not automatically the most

economically efficient under every risk-return regime. SVR's relatively stable performance in this defensive portfolio may be associated with its structural risk minimization principle, which can reduce sensitivity to noisy fluctuations and support generalization in more stable market conditions [10]. This result is also consistent with prior evidence that machine-learning-based portfolio selection can remain competitive when market structures are less dependent on complex long-range or highly non-linear interactions [13, 15]. Accordingly, model selection should be viewed as conditional on portfolio characteristics rather than as a universal ranking of forecasting algorithms.

The findings for P4 and P5 provide additional insight. Returns became negative for most model configurations in the lower-ranked portfolios. In P4, all four strategies generated negative daily returns, while in P5 the DMLP+MSAD portfolio generated a positive daily return of 0.1333 and a positive return-to-risk ratio of 0.34, whereas CNN+MSAD, LSTM+MSAD, and SVR+MSAD remained negative. Rather than necessarily indicating failure of the ranking procedure, the progressively weaker outcomes in the lower quintiles provide evidence that the forecasting models were able to distinguish relatively attractive from relatively unattractive assets. The negative performance of P4 and much of P5 therefore strengthens the interpretation that predicted-return sorting had discriminatory value. Similar logic underlies prediction-based asset preselection strategies, in which forecasting models are used not only to predict exact returns but also to separate stronger investment candidates from weaker ones [8, 9].

The results further support the use of MSAD as the portfolio optimization mechanism. Across the study, AI-generated forecasts embedded in MSAD optimization produced stronger risk-adjusted outcomes than the corresponding equal-weighted benchmark. This suggests that the benefit of the proposed framework arises from the interaction between prediction and risk-sensitive allocation rather than from forecasting alone. Downside-risk measures are advantageous because they focus on unfavorable deviations instead of treating upward and downward variability equally [4]. Recent work on tail-sensitive portfolio optimization similarly emphasizes the need to represent adverse return distributions more explicitly [5], while higher-order portfolio models have shown that moving beyond conventional mean-variance assumptions can improve the representation of non-normal return behavior [3]. The current findings are also consistent with the application of CNN forecasting within an MSAD framework, which demonstrated the usefulness of linking artificial intelligence directly to downside-risk optimization [6].

An additional implication concerns forecast uncertainty. The study confirms that statistical loss functions and portfolio efficiency should be examined jointly. Portfolio weights are highly sensitive to expected-return inputs, meaning that even relatively small forecast errors may produce economically meaningful changes in allocation. Research emphasizing learning from out-of-sample forecast errors has demonstrated that prediction uncertainty should be considered explicitly within portfolio optimization rather than treated as an independent modeling issue [31]. The current study provides further support for this argument. DMLP's lower prediction errors generally translated into superior high-growth portfolio performance, but SVR's stronger result in P2 demonstrates that average forecast accuracy alone was insufficient to determine the best investment model across all settings. This finding reinforces the need for decision-centric evaluation of predictive systems.

More broadly, the findings indicate that portfolio optimization under market uncertainty benefits from matching the predictive architecture to the characteristics of the intended portfolio. Recent quantitative portfolio research emphasizes the importance of adaptive approaches under uncertain and rapidly evolving market conditions [1], and multiscale financial modeling further illustrates that exploitable information may exist at different frequencies

and structural levels [2]. The present study extends this logic by showing that different artificial intelligence models can exhibit specialized economic utility across risk profiles. DMLP was most effective for high-growth portfolios, SVR showed relative strength in a more defensive portfolio, and CNN retained competitive performance in settings characterized by difficult or negative return patterns. Thus, the empirical evidence does not support a one-model-fits-all approach. Rather, it favors an adaptive portfolio architecture in which model selection is connected to risk appetite, expected return, and the underlying characteristics of the asset subset.

This study has several limitations. First, the empirical analysis was confined to equities traded on the Abu Dhabi Securities Exchange and to a defined historical period, including an out-of-sample evaluation focused on 2023; consequently, the observed relationships may differ across other market cycles, especially during severe crises, unusually strong bull markets, or structural regime changes. Second, the predictive inputs were primarily derived from OHLCV variables using a 20-day rolling window, which may have restricted the ability of LSTM to exploit longer temporal dependencies and constrained CNN feature extraction. Third, transaction costs, bid-ask spreads, market impact, taxes, and slippage were not incorporated, meaning that the reported portfolio returns represent model-level economic performance rather than fully net investable performance. Fourth, the study focused exclusively on equities and did not test whether the framework performs similarly across bonds, commodities, foreign exchange, cryptocurrencies, or mixed-asset portfolios. Finally, the comparison was restricted to DMLP, CNN, LSTM, and SVR; therefore, the findings cannot establish superiority relative to more recent architectures such as transformers, attention-based models, graph neural networks, or ensemble systems.

Future research should extend the analysis across longer time horizons and multiple market regimes to determine whether the relative advantages of DMLP, CNN, LSTM, and SVR remain stable during bullish, bearish, high-volatility, and crisis periods. Researchers should incorporate broader feature sets that include technical indicators, firm fundamentals, macroeconomic variables, interest rates, oil prices, exchange rates, news sentiment, and investor-attention measures. Longer and adaptive look-back windows should also be tested, particularly for LSTM and other sequence-based models. Future studies may compare MSAD with CVaR, expected shortfall, drawdown-based measures, and other tail-risk criteria and should explicitly incorporate transaction costs and liquidity constraints. Hybrid and ensemble architectures combining DMLP, CNN, LSTM, and other advanced models may further improve robustness. Cross-market validation involving other Gulf Cooperation Council markets and developed and emerging exchanges would also provide evidence regarding external validity. Finally, future work should evaluate rolling or dynamic model-selection mechanisms that automatically identify the most appropriate predictive model for each market regime or portfolio risk profile.

Portfolio managers and investment analysts may use the proposed framework as a decision-support system rather than relying on a single forecasting model for all investment objectives. For growth-oriented portfolios, DMLP-based forecasts can be prioritized when recent market information exhibits strong non-linear patterns, while SVR may be considered when stability and defensive allocation are more important. CNN-based models may be useful when short-term local structures dominate asset behavior. Practitioners should integrate predicted returns with downside-oriented risk measures such as MSAD instead of allocating capital solely according to point forecasts or historical averages. Securities can also be ranked into return-based groups before optimization so that portfolio managers can separate attractive opportunities from lower-quality candidates. In operational applications, model performance should be monitored continuously using both forecasting errors and realized return-to-risk outcomes, and portfolio weights should be recalibrated whenever the prevailing market regime or investor risk tolerance changes.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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