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Neural Investing (Trading): Harnessing Artificial Neural Network for Stock Market Strategies

Ibrahim Kholilul Rohman
Ibrahim.kholilul@ifg.id
Senior Research Associate / Universitas Indonesia

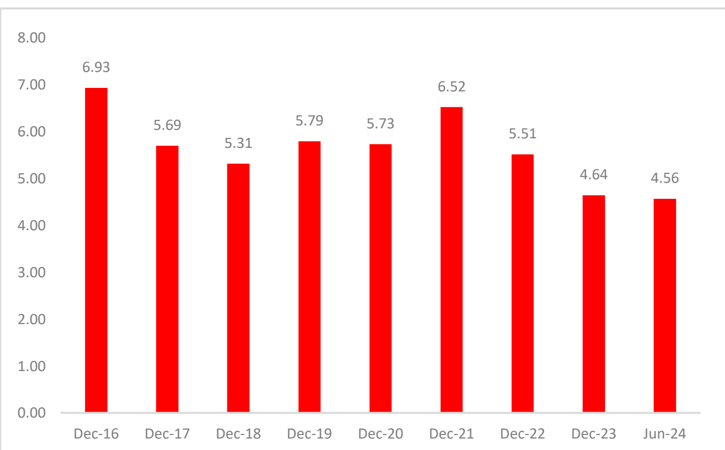
Afif Narawangsa Luviyanto
Afif.narawangsa@ifg.id
Research Associate

- Convolutional Recurrent Neural Networks (CRNN) outperform other models in maximizing cumulative returns, while Transformers and Self-Attention models excel in risk-adjusted returns and drawdown minimization.
- Energy and Health sectors show strong upward momentum with favorable risk-adjusted returns, making them ideal for long-term Buy & Hold strategies. Financial, Consumer Non-Cyclical, and Industrial sectors exhibit mixed performance with periods of recovery and volatility, while Basic Materials, Consumer Cyclical, Property, and Technology sectors experience higher drawdowns and market fluctuations, requiring active monitoring and dynamic strategies.
- Machine Learning (ML)-based technical analysis reacts more quickly to short-term price movements, generating frequent buy and sell signals. Market-driven strategies rely on fundamental analysis and macroeconomic trends, offering a more stable long-term approach to portfolio management.
- To maximize investment performance, future research should focus on: 1. Real-time model updates – ensuring adaptability in volatile markets. 2. Sentiment Analysis Integration – leveraging social media and financial news. 3. Hybrid AI models – combining reinforcement learning with ANN for dynamic decision-making. Integrating sentiment analysis from news and social media can enhance predictive accuracy by capturing broader market sentiment.
- Combining reinforcement learning with ANNs could optimize trading strategies by adapting to market trends dynamically. Regular model recalibration with updated financial data is essential to ensure consistent investment performance and risk management.

Introduction

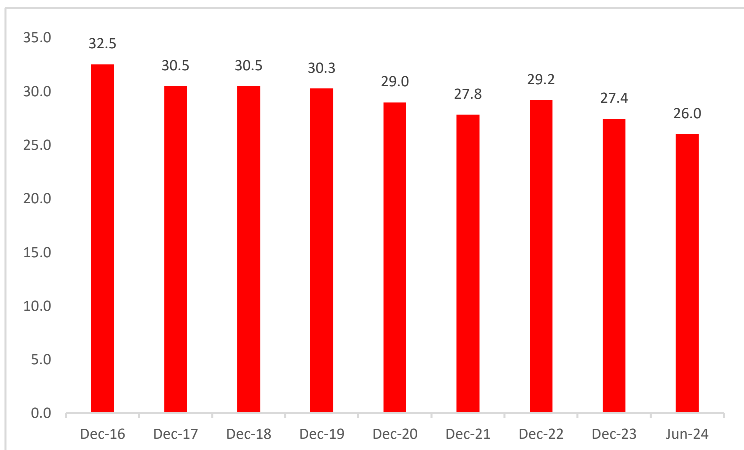
The complexity of capital market investments has increased significantly with the rapid pace of financial innovation, leading to higher risks and potential financial losses. Historically, various institutions have suffered tremendous losses due to overexposure to volatile financial instruments and aggressive equity-linked investments. For example, companies such as American International Group (AIG), Scottish Re Group, The Hartford Financial Services group, and PT Asuransi Jiwasraya, have faced massive financial setbacks largely attributed to poor investment choices, particularly within capital market. AIG reported a loss exceeding $99 billion in 2008 including $21 billion due to declines in equity investments and exposure to credit default swaps (CDS) and mortgage-backed securities (MBS)[1][2]. Similarly, Scottish Re Group has suffered loss of $2,71 billion in 2008[3], largely due to their exposure to declining equity markets. The company's investments were heavily tied to market performance, exacerbating their losses and limiting their ability to manage the associated risks effectively. The Hartford Financial Services Group, meanwhile, reported a staggering $2,7 billion net loss in 2008 compared to net income of $2,9 billion in 2007[4]. The global financial crisis led to declines in their equity portfolios and significant impairments in investments related to their financial services and life insurance sectors, particularly their variable annuity business, which was severely impacted by market turmoil.

Exhibit 1. Percentage of Stock to Total Portfolio Investment of General Insurance (%)



Source: OJK

Exhibit 2. Percentage of Stock to Total Portfolio Investment of Life Insurance (%)



Source: OJK

The declining trend in stock investments as a percentage of total portfolio investments in both general and life insurance sectors further highlight the increasing cautiousness of insurers in managing market risks. As seen in the data from Indonesia's Financial Services Authority (OJK) (Exhibit 1 & 2), the

[1] McDonald, R., & Paulson, A. L. (2014). AIG in Hindsight, Working Paper 2014-07.
[2] https://insight.kellogg.northwestern.edu/article/what-went-wrong-at-aig
[3] https://www.royalgazette.com/re-insurance/business/article/20170526/scottish-re-to-wind-up-after-long-struggle/
[4] https://www.insurancejournal.com/news/national/2009/02/06/97677.htm

percentage of stock investments in general insurance portfolios has dropped from 6.93% in December 2016 to 4.56% in June 2024, while in life insurance, the allocation has decreased from 32.5% to 26% over the same period. This shift indicates a move away from high-risk equity-linked investments, reflecting lessons learned from past financial crises and institutional failures.

The Indonesian financial landscape has recently witnessed a cascade of institutional collapses within its insurance industry, exposing critical vulnerabilities linked to governance deficits and speculative investment practices. Among the most prominent cases is PT Asabri (Persero), a state-owned insurer responsible for managing pensions and insurance portfolios for military and police personnel. Forensic audits revealed cumulative losses exceeding USD 1.6 billion (IDR 23.7 trillion) between 2012 and 2019, attributable to maladministration and fraudulent equity schemes orchestrated by corporate insiders. These activities, involving manipulated transactions in overvalued securities, precipitated criminal prosecutions and highlighted systemic weaknesses in oversight mechanisms.[5]

Concurrently, PT AJB Bumiputera 1912, a century-old life insurance entity, faced insolvency due to chronic liquidity shortfalls and governance lapses. By 2020, actuarial miscalibrations and an obsolete business model had culminated in a deficit surpassing USD 1.4 billion (IDR 20 trillion), starkly contrasting with the equity-driven collapses of Asabri and PT Asuransi Jiwasraya. Bumiputera's decline underscores the sector's failure to align actuarial frameworks with contemporary financial dynamics, exacerbating solvency risks.[6]

These cases collectively illuminate systemic deficiencies within Indonesia's insurance architecture, characterized by lax regulatory enforcement, inadequate risk-assessment protocols, and a propensity for speculative capital allocation. Investigations by Indonesia's Financial Services Authority (OJK) and Audit Board (BPK) have elucidated entrenched financial malpractices, including collusion among stakeholders to bypass investment safeguards. The recurrence of such crises has spurred regulatory reforms aimed at enhancing transparency, including stricter capital adequacy requirements and mandatory stress-testing for high-risk portfolios.

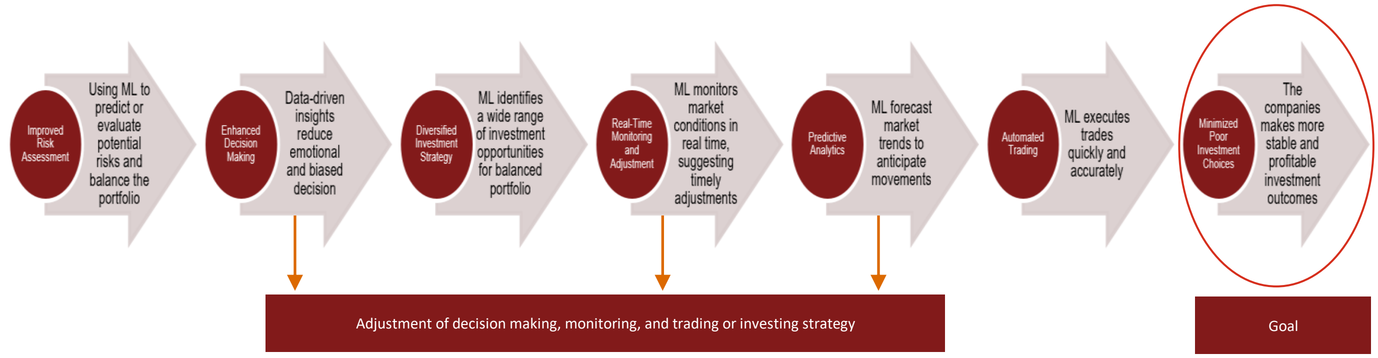
The key challenge for investors lies in reducing inherent risks of capital market such as stock market exposure while still securing optimal returns. Traditional approaches have often failed in managing the volatility and complexity of today's financial markets, as demonstrated by the losses that have happened in various institutions. In response to this challenge, advanced computational techniques such as Artificial Neural Networks (ANNs) present a promising alternative, offering more sophisticated and effective strategies to navigate the complexities of stock market investment.

The Role of Machine Learning in Investment Decisions

Machine Learning (ML) helps reduce financial losses by improving investment decisions. As shown in exhibit 3, ML introduces a data-driven framework that not only enhances decision-making but also provides the flexibility and speed needed to adapt to fast-changing market dynamics.

[5] https://www.reuters.com/world/asia-pacific/indonesia-corruption-court-jails-executives-insurer-20-years-2022-01-05/
[6] https://ojk.go.id/en/kanal/iknb/berita-dan-kegiatan/siaran-pers/Pages/Press-Release-OJK-Beefs-Up-Insurance-Industry%2C-Replacing-AJB-Bumiputera-1912-Management.aspx?

Exhibit 3. Machine Learning Step to Improve Investment Strategy



Source: IFGP Research Analysis

The first stage, improved risk assessment, involves using ML to predict or evaluate potential risks by analyzing large datasets and market trends, helping investors maintain balanced portfolios (Pathek et al., 2023). This approach is highly operated in algorithmic trading, where ML models are used for real-time risk management and mitigation. Following risk assessment, Enhanced Decision-Making is driven by ML-generated data insight, which minimizes the influence of emotional and biased decisions and lead to more data-driven investment choices (strader et al., 2020). These insights are applied to support a Diversified Investment Strategy, where ML identifies a wide range of investment opportunities, helping spread risk across different sectors and asset classes (Novykov et al., 2023).

In the Real-Time Monitoring and Adjustment stage, ML monitors the condition of real-time market and recommends timely adjustments to optimize portfolios, ensuring that investments align with market dynamics (Karhik, 2023). Predictive Analytics, a key function of ML, forecasts future market trends, allowing investors to anticipate market movements (Aljohani, 2023). The forecast future market trends lead to Automated Trading, where ML is used to execute quick market trading and minimizing human error to accommodate dynamic markets (Ta et al., 2018). Finally, by leveraging ML at each stage of investment decisions, companies could minimize poor investment choices, resulting in more stable outcomes.

In this study, we focus on several questions to answer which method is suitable for processing data with the result of buy, hold, or sell decisions on equity market.

1. How is ML being used to analyze equity market data?
2. What are and how many methods in ML that we could use to analyze equity market data?
3. How can Artificial Neural Networks (ANN) be utilized to optimize buy, hold, and sell decisions by evaluating return and risk, and how can this strategy be effectively implemented using real sample data?

How Machine Learning Models Analyze Market Data

The broader role of ML in investment strategies extends into specific methodologies like fundamental analysis, sentiment analysis, and algorithmic trading, which leverage ML's data-processing capabilities for precise financial insights. ML's application in fundamental analysis combines financial metrics with predictive algorithms, enhancing stock price forecasts. In sentiment analysis, ML models interpret market sentiment from news and other text sources, adding a qualitative layer to quantitative data. Algorithmic trading utilizes reinforcement learning to adapt strategies to volatile markets. These ML methodologies collectively demonstrate how advanced data-driven approaches enhance traditional investment practices, enabling more informed and adaptive decision-making.

The literature highlights various machine learning (ML) methodologies for enhancing investment strategies through data analysis and predictive modeling. Fundamental Analysis is a key approach, as illustrated by Lu and Zhou, where ML techniques combined with financial indicators improve stock price prediction accuracy. Their study showcases the role of ML in integrating quantitative financial metrics with analytical algorithms to derive more reliable predictions (Huang, Capretz, & Ho, 2021). Another application lies in Sentiment Analysis, where Wang, Zhang, and Huang utilize deep learning models, specifically Long Short-Term Memory (LSTM) networks, to forecast stock movements based on financial news sentiment. This approach demonstrates ML's ability to interpret non-numerical data, such as text sentiment, enhancing prediction models with a new layer of market insight (Vargas et al., 2017).

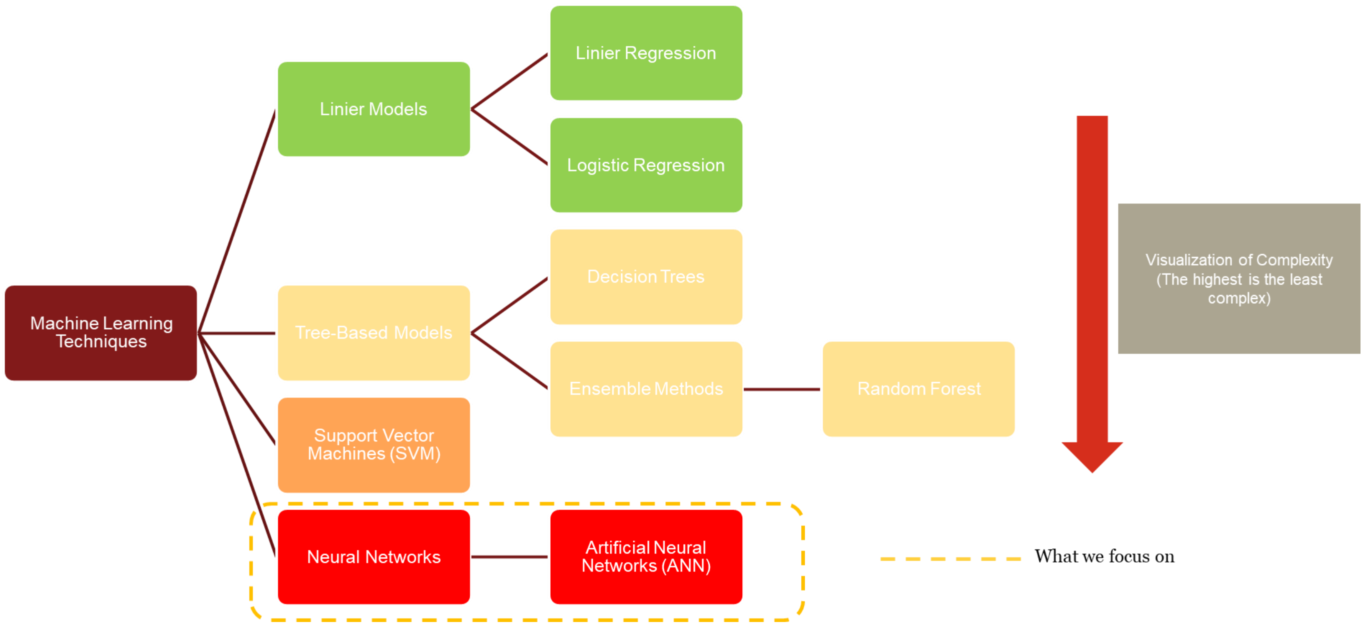
In Algorithmic Trading, Li, Zheng, and Zheng (2019) propose a deep robust reinforcement learning (DRRL) framework, which addresses the limitations of traditional trading algorithms in unpredictable financial markets. Their work underscores how combining deep learning with reinforcement learning creates adaptive strategies that can handle market volatility and improve trading performance (Li, Zheng, & Zheng, 2019). Finally, Technical Analysis Optimization is explored by Ayala et al., who optimize technical analysis strategies in stock indices using ML models. This research highlights the value of ML in refining predictive techniques, showing that it can enhance the performance of strategies traditionally based on historical price trends (Ayala et al., 2021).

This body of work underscores ML's versatility in the financial sector, spanning fundamental analysis, sentiment-based predictions, algorithmic trading, and technical strategy optimization. Collectively, these studies illustrate ML's role in transforming traditional financial analysis into adaptive, data-driven methodologies capable of responding dynamically to market conditions.

Hierarchy of Machine Learning Techniques for Financial Applications

In the progression of machine learning (ML) applications in financial analysis and investment strategies, choosing the appropriate technique is critical for optimizing outcomes based on the complexity and nature of the task. Different ML models bring distinct approaches and computational demands, allowing for tailored applications depending on data and prediction requirements. The following hierarchy represents various ML models in terms of complexity, from simpler linear models to more advanced neural networks, emphasizing the diverse capabilities of these techniques. Exhibit 4 shows the level of complexity among the machine learning techniques to analyze investment decisions based on the market data

Exhibit 4. Hierarchy of Machine Learning Complexity



Source: Various sources, IFGP Research Analysis

Linear Models, such as linear and logistic regression, represent the least complex category. These models are effective for straightforward relationships, relying on linear dependencies between variables to make predictions. Tree-Based Models, such as decision trees, introduce hierarchical structures, enabling more nuanced interpretations of data through binary splitting rules. Ensemble Methods, specifically Random Forests, build on the decision tree framework by combining multiple trees to enhance prediction accuracy and reduce overfitting, thus offering a balance between complexity and performance (Fernández-Delgado et al., 2014). The ensemble approach is further enhanced by methods like stacking, where multiple base classifiers such as Random Forest and SVM are combined to increase accuracy (Jiang et al., 2019).

Support Vector Machines (SVM) represent a further step up in complexity, particularly when non-linear kernels are applied. SVMs excel in classification tasks by defining optimal boundaries in high-dimensional space, which requires significant computational power and careful tuning. At the highest level of complexity are Neural Networks and Artificial Neural Networks (ANN), which are powerful for capturing intricate patterns and non-linear relationships within large datasets. However, they demand extensive computational resources and are typically employed in complex predictive tasks, including time-series forecasting and sentiment analysis.

In synthesizing the characteristics, advantages, and limitations of various machine learning models, a detailed comparison becomes essential to guide model selection based on specific analytical goals and data complexities. The following summary (exhibit 5) provides a structured overview of key machine learning techniques from linear regression to neural networks highlighting their strengths and weaknesses.

Exhibit 5. Comparison of Machine Learning Models: Characteristics, Advantages, and Limitation

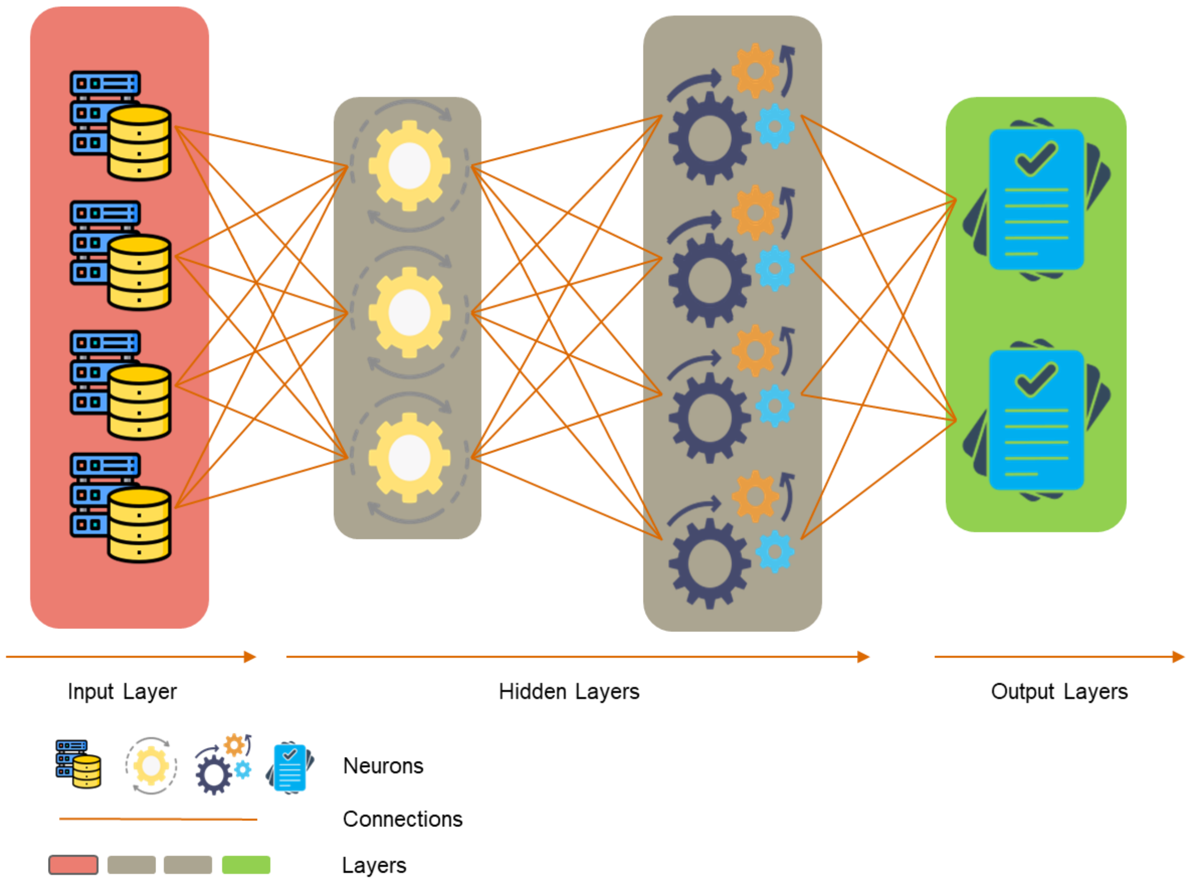
Models	Techniques	Description	Pros	Cons	References
Linier Models	Linier Regression	Linear regression models the relationship between a dependent variable and one or more independent variables by fitting a linear equation to observed data, predicting continuous outcomes.	Simple and easy to understand, computationally efficient, Interpretable coefficients.	Assumes a linear relationship between variables, Sensitive to outliers, Limited ability to capture complex patterns.	**Desgagné, A.** (2021). *Efficient and robust estimation of regression and scale parameters, with outlier detection*
	Logistic Regression	Logistic regression is used for binary classification tasks, modeling the probability of a binary outcome (e.g., stock price going up or down) based on predictor variables.	Effective for binary classification, provides probabilistic outputs, Easy to implement and interpret.	Assumes linearity in the log-odds, not suitable for non-linear relationships, can be impacted by multicollinearity.	**Asar, Y.** (2017). *Some new methods to solve multicollinearity in logistic regression*
Tree-Based Models	Decision Trees	Decision trees are a non-linear model used for classification and regression tasks. They split the data into subsets based on feature values, creating a tree-like structure where each node represents a decision rule, and each branch represents an outcome.	Easy to understand and interpret, can handle both numerical and categorical data, Non-linear relationships between variables can be captured.	Prone to overfitting, can be unstable with small variations in data, Requires significant computational resources for large datasets.	**Liu, W., & Tsang, I.** (2017). *Making Decision Trees Feasible in Ultrahigh Feature and Label Dimensions*
	Random Forest	An ensemble learning method that constructs multiple decision trees during training and outputs the average prediction (regression) or the majority vote (classification) of the individual trees. It improves predictive accuracy and controls overfitting.	Reduces overfitting compared to individual decision trees, Handles large datasets and high dimensionality robust to noise in the data.	Less interpretable than individual decision trees, computationally intensive, Requires careful tuning of hyperparameters.	**Wang, H.** (2023). *Research on the Application of Random Forest-based Feature Selection Algorithm in Data Mining Experiments.*
Support Vector Machines (SVM)	Support Vector Machines (SVM)	A supervised learning algorithm used for classification and regression tasks. It finds the hyperplane that best separates the data into classes. For non-linear data, SVM uses kernel functions to transform the data into a higher dimension where a hyperplane can be applied.	Effective in high-dimensional spaces, Robust to overfitting in high-dimensional feature spaces, Versatile with different kernel functions.	Memory-intensive for large datasets, Choosing the right kernel can be complex, less interpretable than simpler models.	**B. Üstün, W. Melssen, & L. Buydens** (2006). *Facilitating the application of Support Vector Regression by using a universal Pearson VII function based kernel*
Neural Networks	**Artificial Neural Networks (ANN)**	**Computational models inspired by the human brain, consisting of layers of interconnected nodes (neurons). They are capable of learning complex patterns through training with large datasets and are used for various tasks including classification and regression.**	**Can model complex, non-linear relationships, highly flexible and adaptable to various types of data, Capable of learning from large datasets.**	**Requires large amounts of data and computational power, Prone to overfitting without proper regularization, Difficult to interpret and understand the internal workings (black-box nature).**	**Jia, X., Yang, J., Liu, R., Wang, X., Cotofana, S., & Zhao, W.** (2020). *Efficient Computation Reduction in Bayesian Neural Networks Through Feature Decomposition and Memorization.*

Source: Various sources

Artificial Neural Network

Following our comparison of various machine learning models, this part will discuss specifically on Artificial Neural Networks (ANNs). Known for their complexity and versatility (exhibit 2 & 3), ANNs can manage intricate, non-linier patterns within large datasets through multi-layered structure. Their adaptability and high predictive accuracy make them particularly suited for complex tasks. This section will explain deeply into the architecture of ANNs, detailing how each layer contributes to transforming raw input data into actionable decisions.

Exhibit 6. Architecture of Artificial Neural Network (ANN)



Source: Zhu, A. X. (2016). Artificial neural networks. International Encyclopedia of Geography: People, the Earth, Environment and Technology: People, the Earth, Environment and Technology, 1-6.

Exhibit 6 explains the ANN multiple interconnected layers that process input data to generate prediction or decisions. This structure is broadly organized into three main components: input layer, hidden layer, and output later. Each of layers serves distinct functions in the information process.

The input layer is the initial stage that receives the raw data from the database. Each neuron in this layer represents an individual feature of the input data, essentially preparing the information to be passed through the network without performing any significant transformations.

The hidden layers are the core of ANN, responsible for learning complex patterns and relationship within the data. Each hidden layer consists of multiple neurons interconnected by weighted connection, which are adjusted during training to minimize error. These weights represent the strength of each connection, allowing the network to transform input data into more abstract representations. The complexity of an ANN increases with the number of hidden layers and neurons, making it to capture non-linier patterns.

Finally, the output layer provides the network's final prediction or decision based on the processed data. The output layer translates the learned data transformations into a form that aligns with the specific problem being addressed, making ANN versatile for various tasks.

The interconnected structure of layers in an ANN stimulates the aspects of human learning by adjusting weights based on error feedback, a process driven by algorithms. However, the model's complexity also introduces challenges, such as the requirement for large computational resources and protentional overfitting, particularly when the network is deep or trained on limited data.

Hidden Layers of Artificial Neural Networks (ANNs)

To understand deeper about the hidden process of Artificial Neural Networks, it is essential to focus on the hidden layers, where the main processing of complex relationships, non-linier patterns, and data transformations take place. The components which are neurons, weights, and bias play a pivotal role to efficiently enable the network to learn the input data.

As explained in exhibit 4, each neuron in the hidden layers calculating output represented as y. The output is calculated as follows:

$$y = \emptyset \left(\sum_{i=1}^{n} \omega_i \chi_i + \beta\right) \tag{1}$$

- y : Output
- $\emptyset$: activation function
- ω_i : the weights
- χ_i : the inputs
- β : bias

χ_i denotes the input features, ω_i represents the weights, β is the bias, and $\emptyset$ is the activation function that introduces non-linearity to allow the network to capture complex relationships within the data. Each neuron aggregates the weighted inputs, applies the bias, and passes the result through the activation function to produce an output, which then serves as an input for the neurons in the subsequent layer. This cascading effect across layers enables ANNs to learn from data by adjusting these weights and biases, enhancing their ability to detect patterns and make predictions (Cao et al., 2018).

Architecture of Artificial Neural Network

Exhibit 7 illustrates various architectural designs of Artificial Neural Networks (ANNs) applied in the financial sector, particularly in strategizing stock market investment. Each neural network architecture leverages different approaches to handle the complexities and non-linear patterns inherent in stock price movements.

Exhibit 7. Types of Architecture of Artificial Neural Network (ANN)

No	Neural Network	Description	References
1	Convolutional Recurrent Neural Network (CRNN)	This model looks at past stock prices and trends over time, using both spatial (patterns over a period) and sequential (order of prices) data to help decide whether to hold, buy, or sell.	Gao, S., Lin, B., & Wang, C. (2018). Share Price Trend Prediction Using CRNN with LSTM Structure. 2018 International Symposium on Computer, Consumer and Control (IS3C), 10-13. https://doi.org/10.1080/23080477.2019.1605474.
2	Deep Q-Network (DQN)	This model learns the best actions (like holding, buying, or selling) by trying different strategies in a simulated stock trading environment and seeing which ones lead to the most profit over time.	Chen, X., Wang, Q., Yuxin, L., Hu, C., Wang, C., & Yan, Q. (2023). Stock Price Forecast Based on Dueling Deep Recurrent Q-network. 2023 IEEE 6th International Conference on Pattern Recognition and Artificial Intelligence (PRAI), 1091-1096. https://doi.org/10.1109/PRAI59366.2023.10332127.
3	Gated Recurrent Unit (GRU)	GRU is a type of RNN that captures important sequential information in stock prices, making it effective in predicting future price trends based on past data.	Biazon, V., & Bianchi, R. (2020). Gated Recurrent Unit Networks and Discrete Wavelet Transforms Applied to Forecasting and Trading in the Stock Market. . https://doi.org/10.5753/eniac.2020.12167.
4	Long Short-Term Memory with Attention Mechanism (LSTM-AM)	LSTM-AM combines the long-term memory capabilities of LSTM with an attention mechanism that focuses on the most relevant parts of the stock price sequence, improving prediction accuracy.	Qiu, J., Wang, B., & Zhou, C. (2020). Forecasting stock prices with long-short term memory neural network based on attention mechanism. PLoS ONE, 15. https://doi.org/10.1371/journal.pone.0227222.
5	Long Short-Term Memory (LSTM)	LSTM is designed to remember long-term dependencies in sequences of stock prices, allowing it to make more accurate predictions about future market movements.	Fischer, T., & Krauss, C. (2017). Deep learning with long short-term memory networks for financial market predictions. Eur. J. Oper. Res., 270, 654-669. https://doi.org/10.1016/j.ejor.2017.11.054.
6	Self-Attention (SA)	The Self-Attention mechanism analyzes entire sequences of stock prices, assigning importance to different time steps, which allows the model to make informed predictions by focusing on the most critical periods in the data.	Zheng, J., Xia, A., Shao, L., Wan, T., & Qin, Z. (2019). Stock Volatility Prediction Based on Self-attention Networks with Social Information. 2019 IEEE Conference on Computational Intelligence for Financial Engineering & Economics (CIFEr), 1-7. https://doi.org/10.1109/CIFEr.2019.8759115.
7	Temporal Convolutional Network (TCN)	TCN uses convolutional layers to process sequences of stock prices, capturing long-range dependencies and temporal patterns, which helps in accurately forecasting future price movements.	Xiang, X., & Wang, W. (2023). Predicting Intraday Trading Direction of CSI 300 Based on TCN Model. 2023 2nd International Conference on Machine Learning, Cloud Computing and Intelligent Mining (MLCCIM), 293-299. https://doi.org/10.1109/MLCCIM60412.2023.00048.
8	Transformer	Transformers use self-attention mechanisms to process stock price sequences in parallel, identifying complex relationships within the data, making them powerful tools for predicting future market trends.	Li, Y., Lv, S., Liu, X., & Zhang, Q. (2022). Incorporating Transformers and Attention Networks for Stock Movement Prediction. Complex., 2022, 7739087:1-7739087:10. https://doi.org/10.1155/2022/7739087.

Source: Various Sources

Models such as the Convolutional Recurrent Neural Network (CRNN) and Long Short-Term Memory (LSTM) networks emphasize capturing sequential and spatial patterns, which are crucial for analyzing historical stock price trends. Other architectures, like the Deep Q-Network (DQN) and Gated Recurrent Unit (GRU), focus on simulating decision-making strategies and efficiently processing sequential information, thereby enhancing prediction and investing accuracy.

Advanced models, including LSTM with Attention Mechanism (LSTM-AM), Self-Attention (SA), and Transformers, incorporate attention mechanisms, allowing the networks to focus on the most influential time steps within a sequence. This approach improves the model's investing accuracy by identifying critical patterns within complex data. Furthermore, architectures such as the Temporal Convolutional Network (TCN) employ convolutional layers to process longer dependencies, capturing broader patterns that may influence market fluctuations over extended periods. These neural network architectures provide a comprehensive comparison, enabling the identification of optimal models for stock trend prediction in the Indonesian market.

How to Compare Architecture's Performance

As we explain in the previous section about the type of architecture design of ANN, this section explains how to evaluate the performance of each ANN. We use three key indicators which are cumulative return, sharpe ratio, and max drawdown. These metrics provide a comprehensive assessment by covering different aspects of investment performance including return, risk-adjusted returns, and downside risk. The Cumulative Return measures the total return generated by an investment over a specified period, reflecting the overall growth of stock.

$$Cumulative\ Return_t = \sum_{i=1}^{t}(1 + R_i) - 1 \tag{2}$$

- t: is the total number of periods
- R_i : is the return for the *i* – t period

$$Sharpe\ Ratio = \frac{\frac{1}{n}\sum_{i=1}^{n} R_i}{\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(R_i - Average\ Weekly\ Return)^2}} \tag{3}$$

- R_i: *Return*
- $\frac{1}{n}\sum_{i=1}^{n} R_i$: Average Weekly Return
- $\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(R_i - Average\ Daily\ Return)^2}$: Standard Deviation of Weekly Return

The Sharpe Ratio quantifies risk-adjusted returns, helping to determine if the returns justify the investment's inherent risk by comparing returns relative to volatility.

$$Max\ Drawdown = Max_{1 \le t \le T}\left(\frac{Max_{1 \le i \le t} R_i - R_t}{Max_{1 \le i \le t} R_i}\right) \tag{4}$$

- R_t: Cumulative return at time t
- $Max_{1 \le i \le t} R_i$: the maximum cumulative return observed up to time t
- *T: Total number of periods*

Lastly, the Max Drawdown represents the largest observed drop from a peak to a trough in the portfolio's value over the period, offering insights into the potential downside risk and resilience of the investment strategy during adverse market conditions.

Technical Indicators in the ANN Model

This section provides technical indicators used in the main model. We gather companies' data from Bloomberg database. The data is a weekly time series data. The variables which we use are based on Wu et al. (2020). They argue that the core challenge of stock investing is to capture the right time to invest in stock according to the market conditions. Generally, the price open, close, high, low, and volume used to decipher the trends. However, the raw market data contains a higher degree of complexity and noise, which make us difficult to regress overtime even for ANN. To address the problems, technical indicators are extracted from raw data to summarize the market conditions from different perspectives.

Exhibit 8. The List of Used Technical Indicator

Technical Indicator	Indicator Description
MA (5)	Moving Average
EMA (6)	Exponential Moving Average
MACD (7)	Moving Average Convergence/Divergence
BIAS (8)	Bias
VR (9)	Volatility Volume Ratio
OBV (10)	On Balance Volume

Source: Wu, X., Chen, H., Wang, J., Troiano, L., Loia, V., & Fujita, H. (2020). Adaptive stock trading strategies with deep reinforcement learning methods. Information Sciences, 538, 142-158.

The Moving Average (MA) is a technical indicator that smooths out price data by creating a constantly updated average price. This helps in identifying the trend direction. It's commonly calculated over a specific number of periods, such as 10, 20, or 50 periods. In this study, we use weekly data. The formula for a moving average (MA) over periods is:

$$MA = \frac{P_t + P_{t-1} + P_{t-2} + P_t + n}{n} \tag{5}$$

Where P_t represents the closing price for each week *n* is period. MAs are useful for smoothing out short-term fluctuations and identifying long-term trends.

The Exponential Moving Average (EMA) is a type of moving average that gives more weight to recent prices, making it more responsive to new information. The EMA formula for a given period *t* is:

$$EMA_t = EMA_{t-1} + \alpha(P_t - EMA_{t-1}) \tag{6}$$

Where P_t is the price at time *t*, and α is the smoothing factor, often calculated as $\frac{2}{n+1}$ for n periods. EMA is commonly used for analyzing price trends in a more responsive manner compared to SMA.

The MACD is a trend-following momentum indicator that shows the relationship between two exponential moving averages of a stock's price. It is calculated by subtracting the 26-Week EMA from the 12-Week EMA:

$$MACD = EMA_{12} - EMA_{26} \tag{7}$$

A signal line (usually a 9-period EMA of MACD) is plotted on top to signal buy or sell opportunities. When the MACD crosses above the signal line, it indicates a bullish trend; when it crosses below, it signals a bearish trend

Bias is a technical indicator that shows the percentage difference between the current price and a moving average, providing insight into overbought or oversold conditions. The formula is:

$$BIAS = \frac{P_t - MA}{MA} x100 \tag{8}$$

The Volume Ratio (VR) is a technical indicator that incorporates both price changes and trading volume to analyze the strength of a trend. By evaluating how the volume changes as the price moves, VR can provide insights into the momentum behind price movements, helping traders identify potential buying or selling pressure. The formula is:

$$VR = Volume\ x\ \frac{(Close\ Price_t - Close\ Price_{t-1})}{Close\ Price_{t-1}} \tag{9}$$

A positive VR value that grows over time may indicate bullish momentum, as price increases are supported by volume. On the other hand, a declining VR or a shift to negative values can indicate selling pressure, where price decreases are supported by volume.

The On-Balance Volume (OBV) is a momentum-based technical indicator that uses trading volume to predict changes in stock price. It calculates a cumulative volume that adds or subtracts the volume based on the direction of price movement, helping to confirm trends or identify possible reversals. The formula is:

$$OBV = cumsum\ (sign\big(Close.diff(\quad)\big)x\ Volume) \tag{10}$$

A positive On-Balance Volume (OBV) value that grows over time may indicate bullish momentum, as rising prices are supported by increasing volume. This suggests strong buying interest and can be a sign of a sustained uptrend. Conversely, if OBV starts to decline or shifts to negative values, it signals selling pressure, where declining prices are accompanied by higher volume. This pattern indicates that sellers are gaining control, which could lead to a potential downtrend or a reversal.

The Comparison of ANN designs Performance

The results provide an in-depth comparison of various neural network architectures which are CRNN, DQN, GRU, LSTM, LSTM-AM, SA, TCN, and Transformer in terms of their performance across three critical financial indicators: Cumulative Return, Sharpe Ratio, and Max Drawdown. These metrics assess each model's effectiveness in strategizing financial performance and managing associated risks within different sectors and companies. By evaluating the cumulative return, we observe which architectures maximize total returns over time. The Sharpe Ratio provides insights into risk-adjusted performance, identifying models that effectively balance returns with volatility. Finally, Max Drawdown highlights each model's resilience in limiting losses during market downturns. This analysis is intended to determine which architecture excels across various performance dimensions, offering a holistic view of their applicability in financial strategy and investment decision-making.

Exhibit 9. Summary of Cumulative Return Best Performance

Sectors	Indicators	CRNN	DQN	GRU	LSTM_AM	LSTM	SA	TCN	Transform	Best Perform	Neural Network
Consumer Non Cyclical	Cumulative Return	1.167584957	1.068806	1.159713	0.939806	0.950806	1.191806	0.940806	0.960392	1.191806	SA
Consumer Non Cyclical	Cumulative Return	0.472790979	0.366963	0.583863	0.432791	0.430791	0.682791	0.430791	0.663378	0.682791	SA
Energy	Cumulative Return	0.689491641	2.580068	-0.00256	0.02578	0.121598	-0.0714	0.017598	0.159499	2.580068	DQN
Energy	Cumulative Return	1.698015871	0.051455	0.900108	1.569293	1.573293	1.570293	1.569293	2.046792	2.046792	Transform
Financial	Cumulative Return	2.762101374	2.542906	1.233632	1.198717	0.972717	0.967717	0.968717	1.173036	2.762101	CRNN
Financial	Cumulative Return	3.537955068	2.076751	1.64861	2.44711	2.31111	2.29611	2.29711	2.870611	3.537955	CRNN
Healthcare	Cumulative Return	8.708517496	1.013216	-6.70566	7.798625	7.852625	7.875625	7.777625	-1.94221	8.708517	CRNN
Healthcare	Cumulative Return	2.477949435	2.373263	1.606336	1.889282	1.909282	1.722282	1.844282	1.778266	2.477949	CRNN
Industrial	Cumulative Return	6.438910842	6.07695	3.020445	3.207562	3.094562	3.180562	2.978562	2.968208	6.438911	CRNN
Industrial	Cumulative Return	2.04297183	2.798446	0.204964	0.117749	0.085749	0.092749	0.085749	0.163651	2.798446	DQN
Telecommunication	Cumulative Return	1.26479184	1.198443	0.875035	0.956276	1.015276	1.148276	0.896276	0.92844	1.264792	CRNN
Telecommunication	Cumulative Return	2.580290004	26.00247	7.826284	-12.4739	-12.4889	-12.4299	-12.3509	-185.177	26.00247	DQN
Properties	Cumulative Return	3.095729939	2.893039	2.617127	2.504308	2.742127	2.532127	2.703127	2.710119	3.09573	CRNN
Properties	Cumulative Return	17.25544204	-50.273	-48.7405	-8.65214	-8.67014	-8.49014	-8.51314	142.4741	142.4741	Transform
Basic Materials	Cumulative Return	2.085601097	1.335804	0.677345	-0.14088	-0.13688	-0.14288	-0.14188	-0.17463	2.085601	CRNN
Basic Materials	Cumulative Return	5.22938568	5.488191	3.190807	3.340163	3.390163	3.533163	3.282163	3.277645	5.488191	DQN
Consumer Cyclicals	Cumulative Return	-0.782270202	-10.6206	-64.7636	-1.24312	-1.36812	-1.20112	-1.36112	-22.413	-0.78227	CRNN
Consumer Cyclicals	Cumulative Return	-12.52724275	-1.06086	-4.92728	-8.09634	-8.09334	-7.97134	14.71601	14.71701	14.71701	TCN

Source: IFG Progress Analysis, the Data is processed by using phyton
Data is collected from Bloomberg
Cumulative return = 1 means 0%, 1,16 means 16% cumulative return (1,16-1)
Sector data is used based on companies which have big market share

The cumulative return results (exhibit 9) reveal that the Convolutional Recurrent Neural Network (CRNN) approach outperforms other architectures across different companies and sectors. With a total score of 9, CRNN is the most effective model for maximizing cumulative returns, indicating a strong adaptability to varied financial data and effective decision-making in stock predictions. This model's superior performance is evident compared to Deep Q-Network (DQN) and Self-Attention (SA), which rank next with 4 and 2 totals, respectively. Other architectures like Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), and Temporal Convolutional Network (TCN) show limited effectiveness in cumulative return, contributing to lower totals.

For individual company performances, CRNN consistently demonstrates the highest cumulative return values, particularly in sectors like Healthcare (Kalbe Farma and Sidomuncul) and Basic Materials (Amman Mineral and Chandra Asri). Notably, Transformers exhibit peak performance for certain companies such as Sumarecon Agung and Impact Pratama in the Properties and Industrial sectors, indicating its specific advantages in these cases.

Overall, the analysis underscores CRNN's dominance in achieving substantial cumulative returns across various companies. This finding suggests that CRNN may offer a more reliable and effective approach to cumulative return maximization in financial forecasting compared to alternative neural network architectures. The presence of diverse neural network architectures across sectors also highlights the varied applicability of machine learning models depending on sector-specific data characteristics and financial dynamics.

In analyzing the Sharpe Ratio, the results (exhibit 9) indicate that the Transform architecture achieves the highest aggregate score, with a total of 4 instances where it provides the optimal Sharpe Ratio across various companies and sectors. This suggests that Transform-based models may offer a slight advantage in producing favorable risk-adjusted returns, making them potentially more reliable for managing portfolio risk. Closely following Transform, CRNN, DQN, LSTM, and SA each appear three times as the best performer, illustrating their effectiveness in achieving significant Sharpe Ratios.

Exhibit 10. Summary of Sharpe Ratio Best Performance

Sectors	Indicators	CRNN	DQN	GRU	LSTM_AM	LSTM	SA	TCN	Transform	Best Perform	Neural Network
Consumer Non Cyclical	Sharpe Ratio	0.77218651	0.711269	0.677198	0.633698	0.640202	0.793343	0.626269	0.627142	0.793343	SA
Consumer Non Cyclical	Sharpe Ratio	0.28166557	0.221442	0.43146	0.236248	0.235144	0.406728	0.256615	0.388896	0.43146	GRU
Energy	Sharpe Ratio	0.14118367	0.476722	0.035214	0.778255	0.145542	-0.07478	0.018429	0.216446	0.778255	LSTM_AM
Energy	Sharpe Ratio	0.51725667	0.011851	0.27215	0.593707	0.595251	0.58884	0.58847	0.808952	0.808952	Transform
Financial	Sharpe Ratio	1.9035916	1.767801	1.312383	1.282932	1.039376	1.043545	1.044361	1.281568	1.903592	CRNN
Financial	Sharpe Ratio	0.45688699	0.234178	0.231881	0.403089	0.381424	0.367368	0.367533	0.519105	0.519105	Transform
Healthcare	Sharpe Ratio	0.82846952	0.116731	-1.43011	0.918249	0.924496	0.921507	0.910039	-0.51733	0.924496	LSTM
Healthcare	Sharpe Ratio	0.75499721	0.758414	0.688015	0.781867	0.79045	0.716047	0.766917	0.739029	0.79045	LSTM
Industrial	Sharpe Ratio	1.60749923	1.612169	1.215483	1.255557	1.210327	1.258402	1.178558	1.179955	1.612169	DQN
Industrial	Sharpe Ratio	2.38396705	2.762792	0.428332	0.448565	0.37538	0.215078	0.198737	0.385198	2.762792	DQN
Telecommunication	Sharpe Ratio	0.47292054	0.457749	0.454878	0.470394	0.500143	0.569586	0.444585	0.486457	0.569586	SA
Telecommunication	Sharpe Ratio	0.07762337	0.924199	0.501895	-0.50472	-0.50531	-0.50209	-0.4989	-1.08412	0.924199	DQN
Properties	Sharpe Ratio	0.85350039	0.823535	0.970626	0.869842	1.015898	0.910423	0.972336	1.008127	1.015898	LSTM
Properties	Sharpe Ratio	0.39417629	-0.6315	-1.32765	-0.29997	-0.30055	-0.29553	-0.29632	0.397105	0.397105	Transform
Basic Materials	Sharpe Ratio	7.57408629	6.925724	3.874025	-0.01479	0.025851	-1.72912	-1.71923	4.91481	7.574086	CRNN
Basic Materials	Sharpe Ratio	1.81052294	1.899769	1.848096	1.869153	1.896272	1.98147	1.840704	1.784117	1.98147	SA
Consumer Cyclicals	Sharpe Ratio	-0.039587	-0.38848	-1.28293	-0.0743	-0.08203	-0.07461	-0.08455	-1.08959	-0.03959	CRNN
Consumer Cyclicals	Sharpe Ratio	-1.0161778	-0.05974	-0.79408	-0.79021	-0.87177	-0.85865	1.486336	1.486427	1.486427	Transform

Source: IFG Progress Analysis, the Data is processed by using phyton
Data is collected from Bloomberg
Sector data is used based on companies which have big market share

The presence of multiple models with similar totals emphasizes that while Transform might have a marginal edge in risk-adjusted returns, CRNN, DQN, LSTM, and SA also provide robust performance, indicating flexibility and resilience in different market scenarios. The diversity of model performance underscores the adaptability of these architectures to specific financial contexts, highlighting their value in risk-sensitive applications. This distribution suggests that while the Transform model is slightly more dominant, several architectures can be reliable options for optimizing the Sharpe Ratio, thereby enhancing decision-making in financial performance management.

Exhibit 11 summarizes the performance of different neural network architectures based on the Max Drawdown metric across various companies and sectors. The SA (Self-Attention) model consistently demonstrates superior performance, frequently achieving the lowest, or most favorable, Max Drawdown values. This suggests that the Self-Attention model is particularly effective at managing risk by limiting significant declines in cumulative returns, making it a preferred choice for scenarios where minimizing drawdown is critical.

Exhibit 11. Summary of Max Drawdown Best Performance

Sectors	Indicators	CRNN	DQN	GRU	LSTM_AM	LSTM	SA	TCN	Transform	Best Perform	Neural Network
Consumer Non Cyclical	Max Drawdown	0.888948194	0.897465	0.892922	0.897465	0.897465	0.878465	0.896465	0.900261	0.878464726	SA
Consumer Non Cyclical	Max Drawdown	0.814239127	0.803342	0.79868	0.815239	0.815239	0.805239	0.815239	0.809521	0.798679535	GRU
Energy	Max Drawdown	4.968721019	4.499443	0.79448	0.007598	0.741255	0.796255	0.775255	0.732951	0.007598337	LSTM_AM
Energy	Max Drawdown	3.656043074	4.970802	4.158824	3.597486	3.593486	3.597486	3.597486	3.333087	3.333087055	Transform
Financial	Max Drawdown	0.659497399	0.653156	0.648051	0.652497	0.661497	0.661497	0.661497	0.655229	0.64805086	GRU
Financial	Max Drawdown	5.376797977	6.576366	6.114998	5.376798	5.375798	5.376798	5.376798	4.840942	4.840941937	Transform
Healthcare	Max Drawdown	6.918965693	8.05333	10.28259	6.917966	6.898966	6.882966	6.924966	7.320071	6.882965693	SA
Healthcare	Max Drawdown	1.662549382	1.60387	1.616414	1.62132	1.62532	1.64032	1.62432	1.640223	1.603870008	DQN
Industrial	Max Drawdown	0.988010876	0.977285	0.979663	0.987011	0.992011	0.990011	0.992011	0.993429	0.977285202	DQN
Industrial	Max Drawdown	0.418688582	0.418156	0.381818	0.387886	0.395886	0.393886	0.395886	0.398248	0.381818277	GRU
Telecommunication	Max Drawdown	1.279406611	1.300514	1.311974	1.322407	1.268407	1.228407	1.325407	1.333979	1.228406611	SA
Telecommunication	Max Drawdown	28.52875558	10.35729	12.85506	28.51576	28.53676	28.53676	28.49976	199.5047	10.35728614	DQN
Properties	Max Drawdown	1.887098194	1.850829	1.610614	1.680749	1.610614	1.610614	1.586614	1.590974	1.58661428	TCN
Properties	Max Drawdown	18.016061	89.4456	62.6772	17.94884	17.95684	17.92784	17.93884	193.7942	17.92783894	SA
Basic Materials	Max Drawdown	0.337663139	0.235483	0.288848	0.338663	0.336663	0.338663	0.337663	0.165271	0.165271033	Transform
Basic Materials	Max Drawdown	1.03473226	1.023989	1.028007	1.030732	1.029732	1.020732	1.034732	1.038246	1.02073226	SA
Consumer Cyclicals	Max Drawdown	18.25362844	37.65009	72.35671	18.24663	18.27763	18.24663	18.27763	29.82695	18.24662844	SA
Consumer Cyclicals	Max Drawdown	21.4697808	11.1292	11.75962	14.7432	14.7432	14.7392	2.45498	2.45498	2.4549797	TCN

Source: IFG Progress Analysis, the Data is processed by using phyton
Data is collected from Bloomberg
Sector data is used based on companies which have big market share

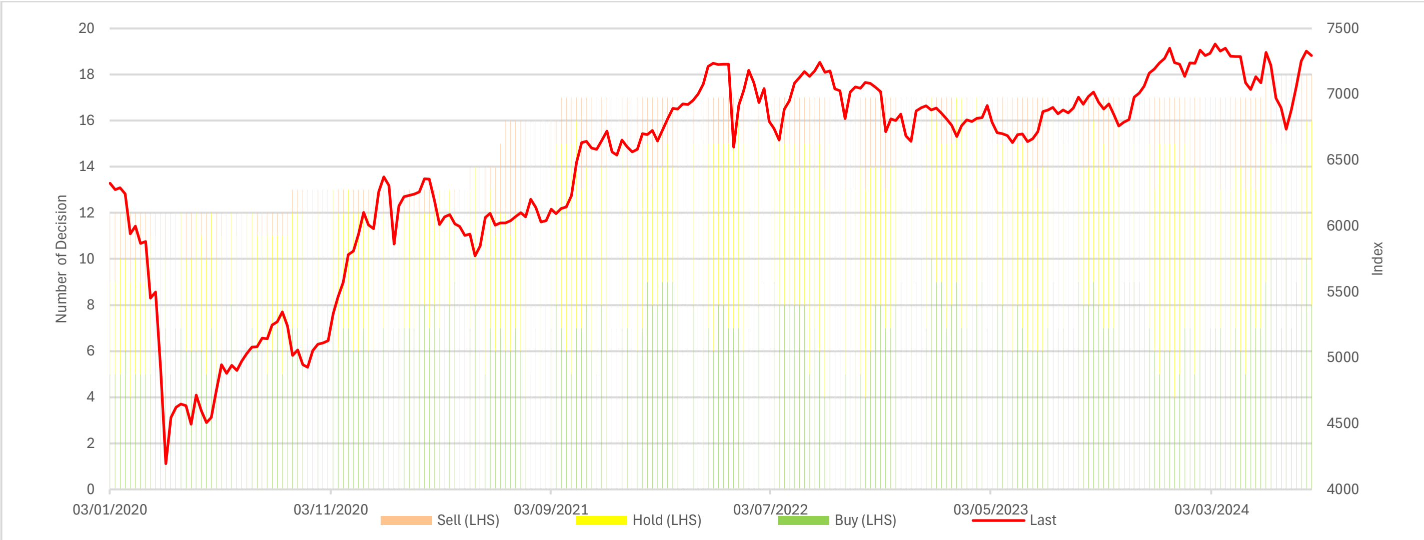
In comparison, other architectures like DQN, GRU, LSTM, and Transform also perform reasonably well, each showing some instances of low Max Drawdown across different sectors. However, their performances are less consistent than those of the Self-Attention model. The CRNN and LSTM-AM architectures have limited success in this regard, indicating they may be less suitable for applications where controlling drawdown is a primary concern.

Based on the analysis across the three performance indicators—Cumulative Return, Sharpe Ratio, and Max Drawdown—the Self-Attention (SA) model emerges as the most balanced and reliable architecture. It consistently achieves favorable results in Max Drawdown, minimizing potential losses across various sectors, which underscores its strong risk management capabilities. Although CRNN shows the best results in terms of Cumulative Return, indicating its effectiveness in maximizing returns, it lacks the same consistency in managing risk as the SA model. Transformer-based models perform well in optimizing the Sharpe Ratio, indicating efficient risk-adjusted returns. Overall, each model has strengths in specific areas.

The Buy, Hold, and Sell Strategy

The analysis of the ANN architecture using Cumulative Return, Sharpe Ratio, and Max Drawdown indicators underscores a strategic preference for Buy, Hold, and Sell actions based on market conditions. The Cumulative Return indicates that holding and buying during favorable periods contributes to steady growth, optimizing returns by taking advantage of market uptrends. The Sharpe Ratio further reinforces this strategy, as the emphasis on buy and hold actions enhances risk-adjusted returns while limiting frequent market exits that could introduce additional volatility. Lastly, the Max Drawdown metric highlights the importance of minimizing reactive selling during downturns, effectively reducing potential losses and preserving capital. This integrated approach of buying during low points, holding for stability, and selectively selling aligns with a robust, risk-managed strategy aimed at maximizing long-term portfolio performance.

Exhibit 12. Summary of Buy, Hold, and Sell for all Sample Companies (2020 – 2024) Maximizing Cumulative Return

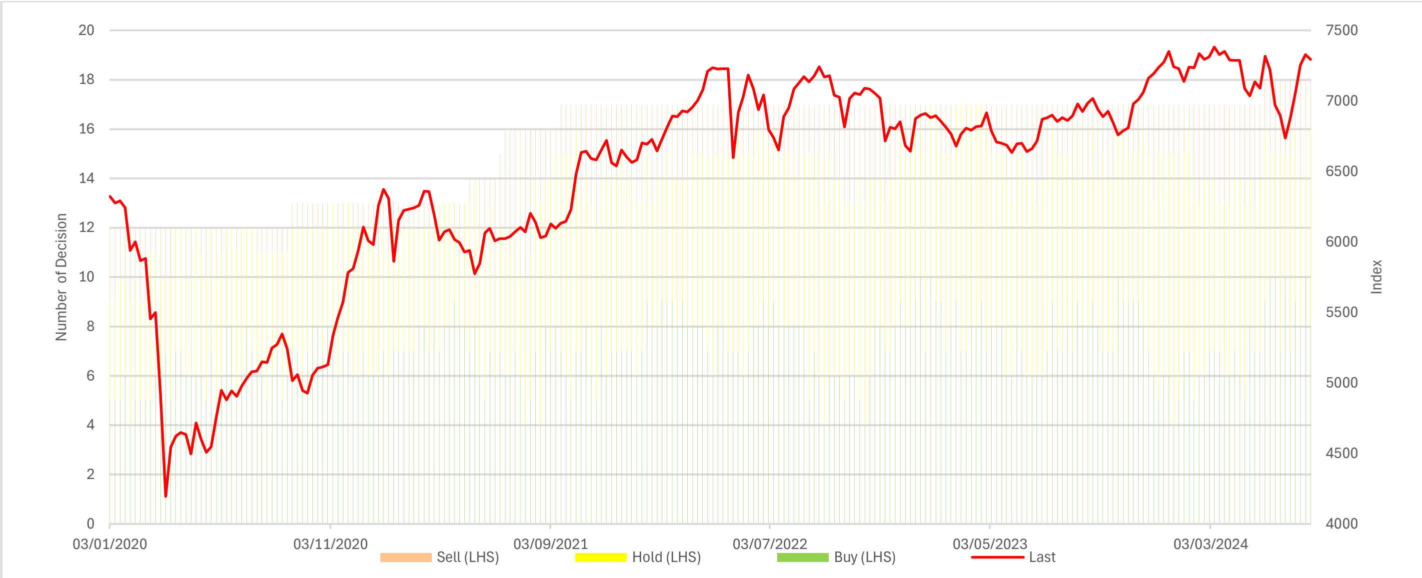


Source: IFG Progress Analysis, the Data is processed by using phyton
Data is collected from Bloomberg

The cumulative return (exhibit 12) illustrates a pronounced preference for the hold and buy strategies, with sell decisions being the least frequent. This distribution suggests a strategic inclination toward maintaining positions during market fluctuations and capitalizing on opportunities by buying during favorable conditions. The higher frequency of buy and hold decisions during periods of market downturn indicates a proactive approach to portfolio management, where the strategy aims to leverage lower price points to maximize long-term returns. The low frequency of sell decisions further implies that the strategy is designed to minimize reactive sales, thereby avoiding potential losses that could arise from premature exit in a volatile market.

The Sharpe ratio (exhibit 13), which adjusts returns relative to risk, also shows a dominance of hold and buy strategies. The predominance of hold indicates a risk-managed approach where positions are maintained to smooth out volatility and capture gains over time. The buy strategy is similarly employed to enhance returns when market conditions suggest potential for growth, thereby contributing to a higher Sharpe ratio. The minimal reliance on sell decisions reflects a strategic focus on preserving positions and optimizing risk-adjusted returns, rather than attempting to time the market frequently, which could introduce additional risk.

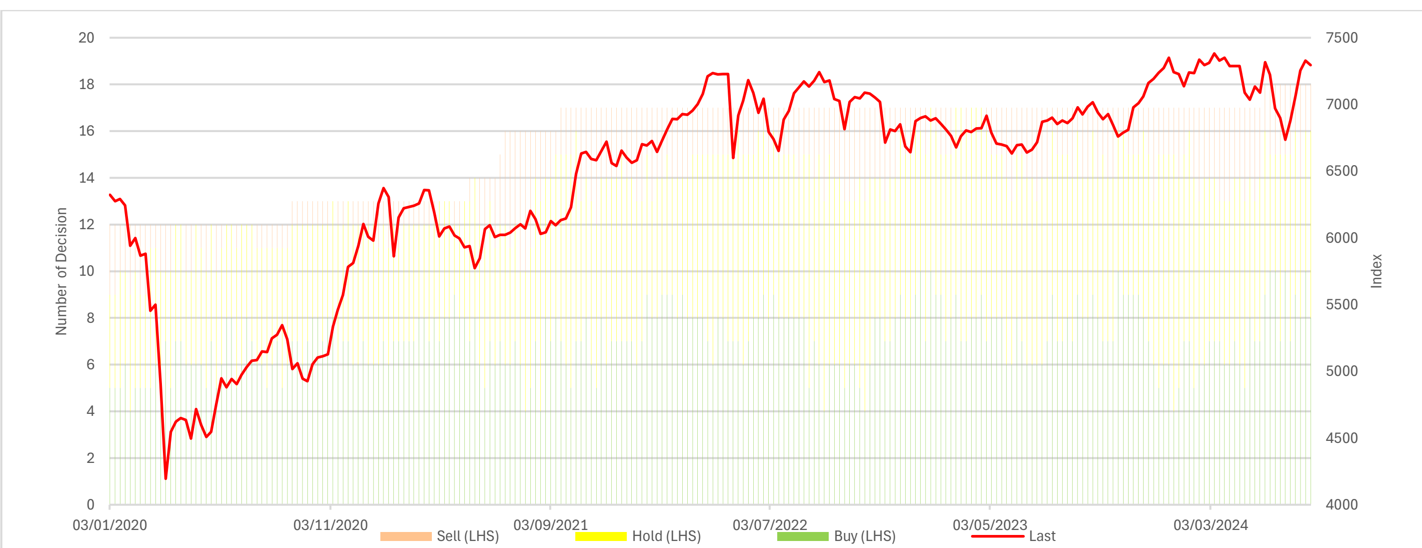
Exhibit 13. Summary of Buy, Hold, and Sell for all Sample Companies (2020 – 2024) Maximizing Sharpe Ratio



Source: IFG Progress Analysis, the Data is processed by using phyton
Data is collected from Bloomberg

The max drawdown metric, which measures the largest peak-to-trough decline, further corroborates the conservative nature of the strategy (exhibit 13). The preference for hold and buy actions during periods of drawdown indicates a calculated approach to mitigate losses by avoiding unnecessary liquidations. By minimizing sell decisions, the strategy effectively reduces the likelihood of realizing losses during temporary market downturns, thus limiting the overall drawdown. This approach aligns with the objective of protecting the portfolio's value while positioning for eventual market recovery.

Exhibit 14. Summary of Buy, Hold, and Sell for all Sample Companies (2020 – 2024) Minimizing Max Drawdown



Source: IFG Progress Analysis, the Data is processed by using phyton
Data is collected from Bloomberg

This analysis of the Artificial Neural Network architecture using Cumulative

Return, Sharpe Ratio, and Max Drawdown reveals a strategic emphasis on buy and hold actions over sell decisions. The cumulative return data shows a preference for maintaining or increasing positions during favorable market conditions to maximize long-term gains. The Sharpe Ratio underscores this approach by emphasizing risk-adjusted returns, where buy and hold actions contribute to more stable, growth-oriented performance. Finally, the Max Drawdown metric confirms the conservative nature of the strategy, as minimizing sell actions during downturns helps limit potential losses, protecting the portfolio's value and positioning it for recovery during subsequent upturns. Together, these metrics highlight a balanced, risk-aware strategy that leverages buy and hold actions to optimize growth and mitigate downside risk.

To complete the study, we also provide a table of strategy buy, hold, and sell for each sector represented by companies chosen based on market capitalization in appendix 1,2, and 3.

Appendix 1 illustrates cumulative return trends for various sectors, accompanied by Buy, Hold, and Sell signals. The Energy and Health sectors display a strong upward momentum, suggesting consistent opportunities for gains, whereas the Technology and Consumer Cyclical sectors face prolonged declines, signaling caution. Sectors like Financial and Property exhibit mixed performance with frequent buy-sell fluctuations, reflecting market uncertainty. The Industrial sector shows initial growth followed by stagnation, indicating sector-specific challenges.

Appendix 2 visualizes sectoral strategies to maximize the Sharpe Ratio, highlighting the balance between risk and return across different sectors. The Energy and Health sectors demonstrate a strong upward trajectory, reflecting favourable risk-adjusted returns, especially during periods with Hold and Buy signals. In contrast, sectors like Property and Technology exhibit prolonged declines, signalled by frequent Sell indicators, showcasing poorer Sharpe Ratio performance. The Financial and Industrial sectors reveal mixed trends with alternating buy-hold-sell periods, suggesting volatility.

The Appendix 3 focuses on sectoral strategies to minimize Maximum Drawdown, which assesses the peak-to-trough decline to manage downside risk effectively. The Energy and Health sectors exhibit the most stable upward trajectories, characterized by long periods of Hold signals and minimal drawdown. Conversely, the Technology and Property sectors display prolonged downward trends, with frequent Sell signals reflecting significant drawdowns and higher volatility. Consumer Non-Cyclical and Financial sectors show mixed performance, experiencing short-term drawdowns mitigated by recovery phases.

The appendices analyse sectoral performance across three key strategies: maximizing cumulative returns, Sharpe Ratio, and minimizing maximum drawdown. The Energy and Health sectors consistently demonstrate strong upward momentum, favourable risk-adjusted returns, and minimal drawdowns, making them the most stable and promising sectors. In contrast, the Technology and Property sectors experience prolonged declines, frequent sell signals, and significant volatility, reflecting poor performance across all strategies. The Financial, Consumer Non-Cyclical, and Industrial sectors show mixed trends, marked by volatility, short-term gains, and recovery phases, indicating sector-specific challenges and opportunities. Overall, Energy and Health outperform, while Technology and Property require caution.

Comparing of Market recommendation with Machine Learning Technical analysis will broaden readers view of how fundamental and technical strategy to maximize the return and minimize the risk. The analysis (Appendix 4) contrasts Machine Learning (ML)-based recommendations, which rely solely on technical analysis, with market-driven buy, hold, and sell strategies that incorporate broader factors like fundamental analysis, macroeconomic trends, and investor sentiment. In stable sectors like Consumer Non-Cyclical, Health, and Telecommunication, ML aligns closely with market recommendations, favoring a buy-and-hold strategy due to consistent price trends. However, in volatile sectors such as Basic Materials and Consumer Cyclical, ML produces more frequent buy and sell signals, reflecting short-term price fluctuations and momentum shifts, while market recommendations tend to favor holding through volatility.

Notably, in Financial and Property sectors, ML often suggests more sell signals, likely due to its reliance on price movements and volume-based indicators, which detect potential downturns earlier than traditional market analysis. However, market-driven recommendations, which include macroeconomic factors and sector fundamentals, may counterbalance ML's technical insights, leading to different investment decisions. This comparison highlights how ML-driven technical analysis can enhance short-term trading strategies, while market-based recommendations may provide a more comprehensive, long-term investment approach.

The analysis (Appendix 5) of Sharpe Ratio-based investment strategies across sectors highlights differences in risk-adjusted returns. Consumer Non-Cyclical, Health, and Telecommunication sectors show consistent buy-and-hold recommendations, indicating strong long-term stability and lower volatility. In contrast, Basic Materials and Consumer Cyclical sectors experience frequent sell signals, reflecting high risk and market fluctuations. Financial and Property sectors demonstrate a mix of hold and sell actions, indicating that market uncertainty impacts their Sharpe Ratio performance.

Machine Learning (ML)-based technical analysis tends to generate more sell signals in volatile sectors, whereas market-driven strategies often favor holding through fluctuations. ML appears more responsive to short-term price movements, while traditional recommendations account for fundamental factors and broader market conditions. This reinforces the importance of sector-specific strategies, where stable sectors benefit from buy-and-hold, while higher-risk sectors require active monitoring and adaptive strategies to optimize risk-adjusted returns.

The Max Drawdown analysis (Appendix 6) highlights sectoral risk exposure and downside resilience. Consumer Non-Cyclical, Health, and Telecommunication sectors exhibit stable buy-and-hold strategies, indicating lower drawdowns and reduced volatility. In contrast, Basic Materials and Consumer Cyclical sectors experience frequent sell signals, reflecting high market fluctuations and significant peak-to-trough declines. Financial and Property sectors also display mixed signals, with periods of strong performance followed by sharp downturns, suggesting higher vulnerability to market shocks.

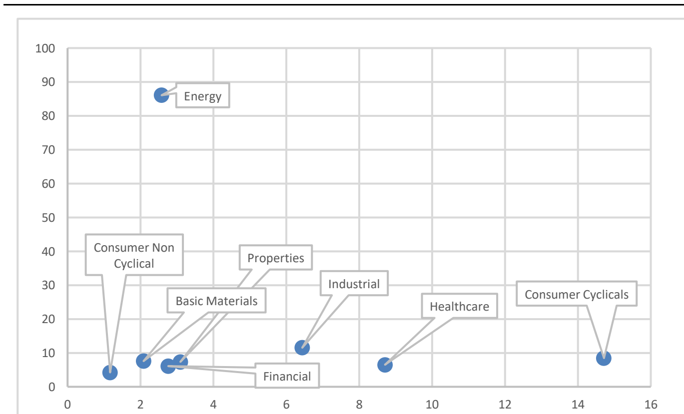
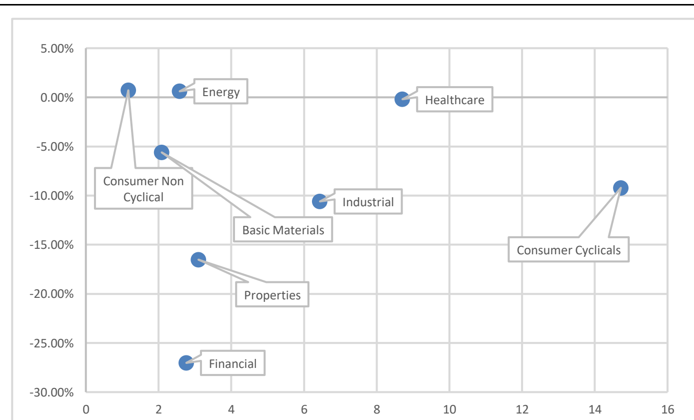
Machine Learning (ML)-based technical analysis generates more sell recommendations in high-risk sectors, whereas market-driven strategies lean towards holding during downturns. ML identifies short-term risk signals effectively, but market recommendations incorporate fundamental insights, balancing risk exposure over time. The findings reinforce the need for sector-specific risk management, where stable industries benefit from buy-and-hold, while volatile sectors require active monitoring and strategic exits to minimize drawdowns.

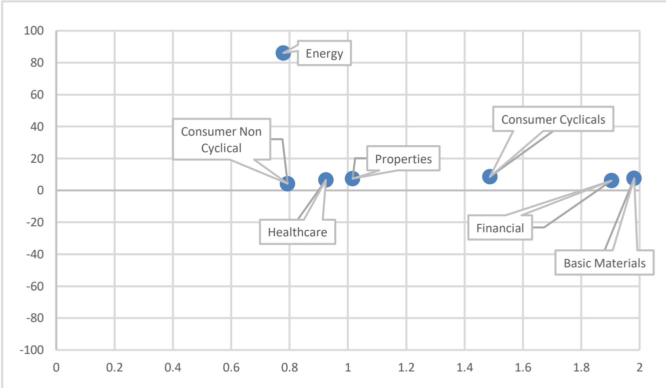
Do not Put Investment in one Basket

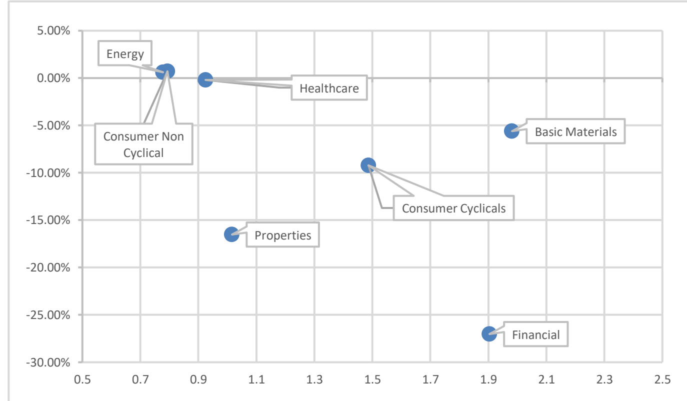
The analysis (Exhibit 14) compares Cumulative Return, Sharpe Ratio, and Max Drawdown (Y-axis) against Volatility and CAGR (X-axis) to assess sectoral investment performance. Energy and Healthcare sectors exhibit higher returns and risk-adjusted performance with relatively lower volatility, making them ideal for long-term investment. Meanwhile, Consumer Cyclical and Financial sectors experience greater drawdowns and negative CAGR, signalling higher exposure to market fluctuations. Basic Materials, Industrials, and Property sectors show mixed results, with some resilience but also periods of instability.

A Buy & Hold strategy appears more effective in maximizing returns while controlling risk, as frequent market exits often increase volatility. The findings emphasize the importance of diversification, where spreading investments across stable and high-growth sectors helps balance risks and returns. By carefully managing exposure based on sector-specific performance trends, investors can optimize their portfolios for both stability and growth.

Exhibit 14. Comparison 3 Indicators of Investment to Volatility and CAGR (2021 – 2024 Volume Transaction)

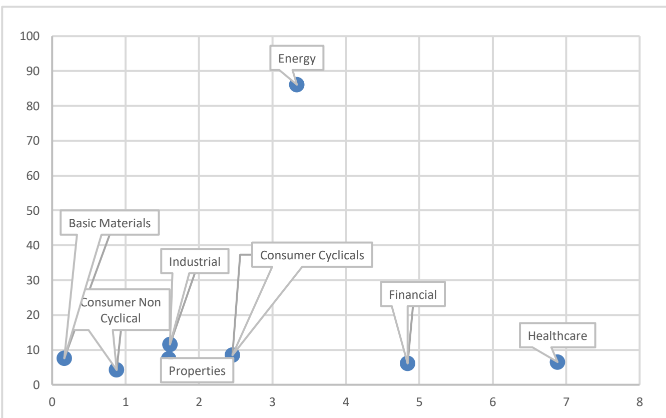
Cumulative Return & Volatility	Cumulative Return & CAGR (2021-2024 Volume of Transaction
	
Sharpe Ratio & Volatility	Sharpe Ratio & CAGR (2021-2024 Volume of Transaction

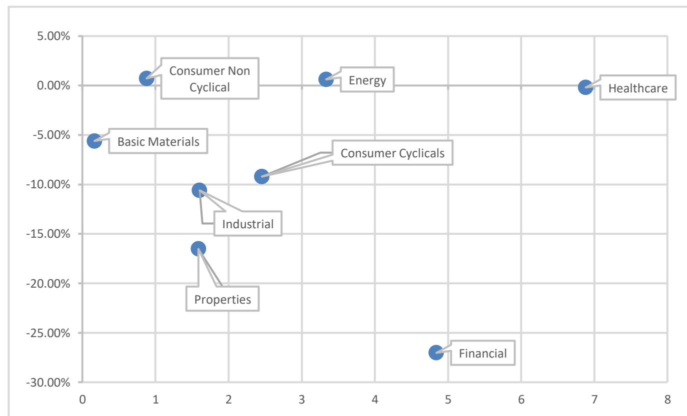




Max Drawdown & Volatility

Max Drawdown & CAGR (2021-2024 Volume of Transaction





Source: IFG Progress Analysis, the Data is processed by using phyton
Data is collected from Bloomberg

Timing the Market or Time in the Market? A Sector-Wide Showdown

This study examines the effectiveness of market-driven recommendations versus Machine Learning (ML)-based investment strategies across sectors using Appendix 4, 5, and 6. Traditional market strategies emphasize fundamental analysis and macroeconomic trends, often favoring a buy-and-hold approach, while ML-driven models leverage data-driven insights to optimize buy and sell timing. The findings reveal that in stable sectors (Health, Consumer Non-Cyclical, Telecommunication), both strategies align closely, supporting long-term holding. However, in volatile sectors (Financial, Industrial, Consumer Cyclical, Basic Materials), ML outperforms by identifying market shifts faster and mitigating drawdowns. This suggests that ML strategies are more suitable for active traders, whereas market recommendations are more effective for passive investors prioritizing stability.

Exhibit 15. Summary of Appendix 4 - 6

Sector	Market Strategy Trends	ML Strategy Trends	Key Insights
Consumer non-cyclical	Mostly hold, buy increased in early 2021, minimal sell.	Consistently high returns, ML optimizes buy timing with earlier sell signals in 2023.	Market favors stability, ML enhances entry-exit points.
Financial	Hold-dominant, increased sell signals in 2022, buy resurging in 2023.	ML detected sell signals earlier, mitigating losses and buying sooner on recovery.	ML adapts better to volatility than market-driven decisions.
Health	Strong buy & hold, few sell signals in late 2022.	ML mirrors market trends, with earlier sell signals.	Both approaches align, ML provides slight risk mitigation.
Industrial	Hold-dominant, buy surged during price dips in 2022, sell rising in late 2023.	ML detected sell-offs faster and signalled buys early in recovery.	ML reacts swiftly to volatility, market delays action.
Property	Hold dominant until mid-2022, then sell increased amid downturns.	ML flagged declining trends earlier, with quicker buy signals post-crash.	ML is more adaptive; market strategy reacts later.
Telecommunication	Mostly hold, minor buy signals, rare sell actions.	ML aligns with market strategies, favouring hold.	Stable sector with minimal differences between approaches.
Basic Materials	High buy & hold in 2021, then sell increased sharply in 2022–2023.	ML detected downturns sooner, issuing more sell signals than market strategies.	ML outperforms in volatile conditions.
Consumer Cyclical	Initially hold-dominant, frequent buy & sell actions in 2022–2023.	ML follows similar patterns, but signals sell earlier in downturns and buy sooner in recovery.	ML improves timing for trading decisions.

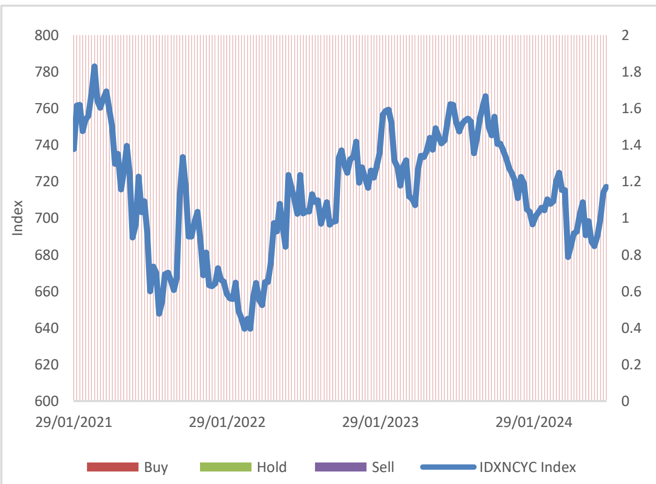
Conclusion and Development

This study highlights the effectiveness of Artificial Neural Networks (ANNs) in optimizing investment strategies, with different architectures excelling in various financial metrics. Convolutional Recurrent Neural Networks (CRNN) outperform others in maximizing cumulative returns, while Transformers and Self-Attention models excel in risk-adjusted performance and drawdown minimization, respectively. The findings suggest that a Buy & Hold strategy is the most effective for long-term stability, particularly in Energy and Health sectors, which consistently generate higher returns with lower volatility. Conversely, Basic Materials and Consumer Cyclical sectors exhibit higher market fluctuations, requiring a more dynamic investment approach. The comparison between Machine Learning (ML) technical analysis and traditional market-driven recommendations reveals that ML is more responsive to short-term price movements, while market strategies incorporate broader economic fundamentals, offering a more balanced long-term perspective.

Future research can further refine ANN-based investment strategies by integrating real-time market adaptation to enhance decision-making during sudden market shifts. Expanding ML models to include sentiment analysis from financial news and social media could provide deeper insights into market psychology, improving predictive accuracy. Additionally, exploring hybrid models that combine reinforcement learning with ANNs could enhance portfolio optimization and risk management. A continuous recalibration of ANN models with updated financial data will be essential to maintain relevance in evolving market conditions and maximize investment performance while minimizing risks.

Appendix 1. Table of Sectoral Strategy maximizing Cumulative return

Consumer Non-Cyclical



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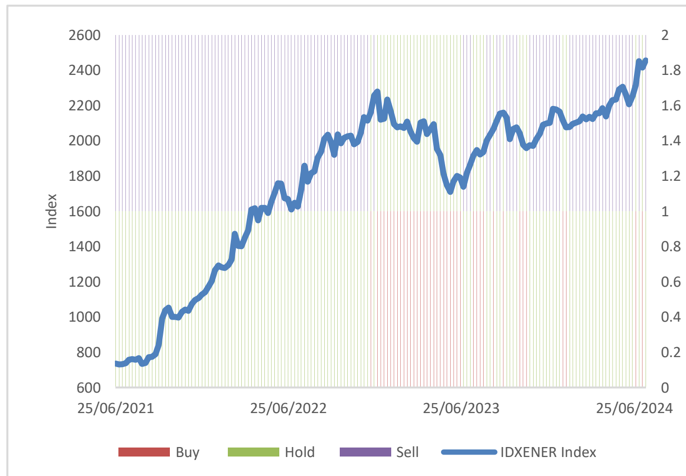

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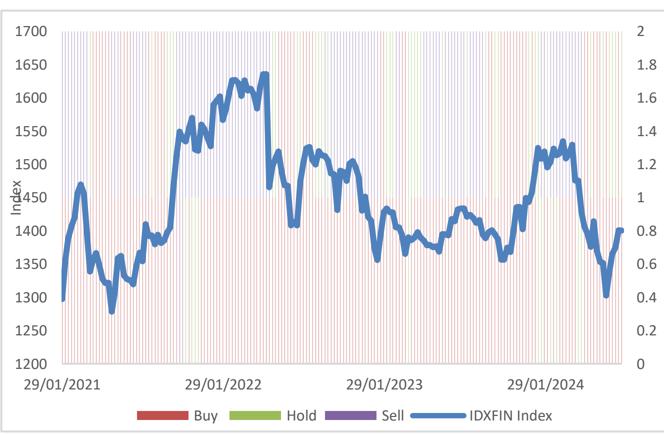

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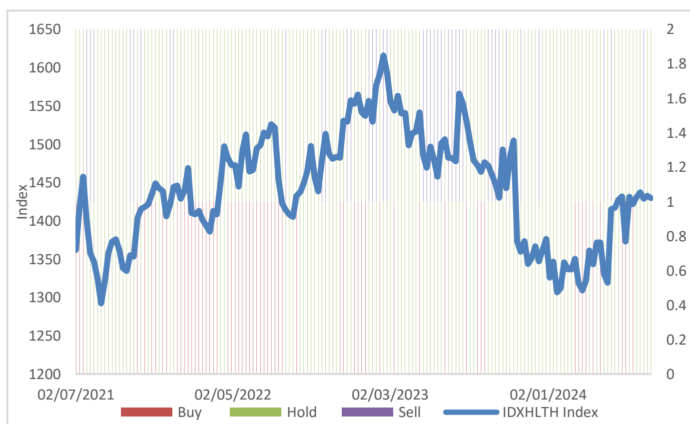
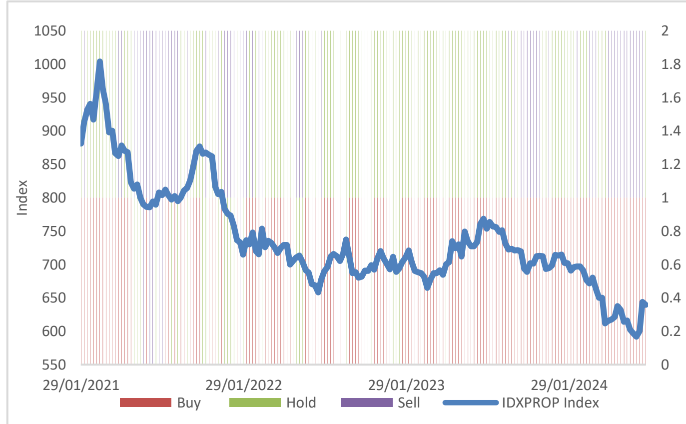
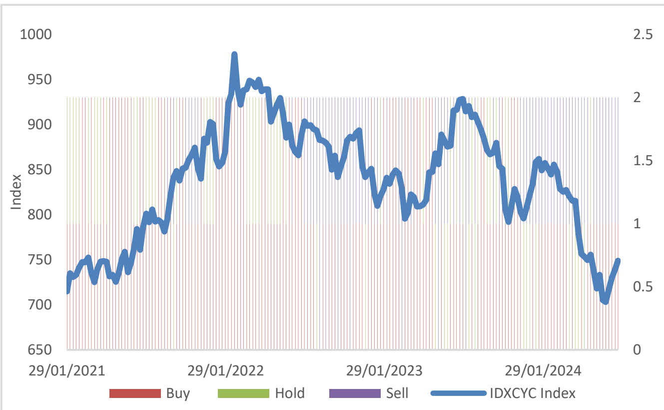


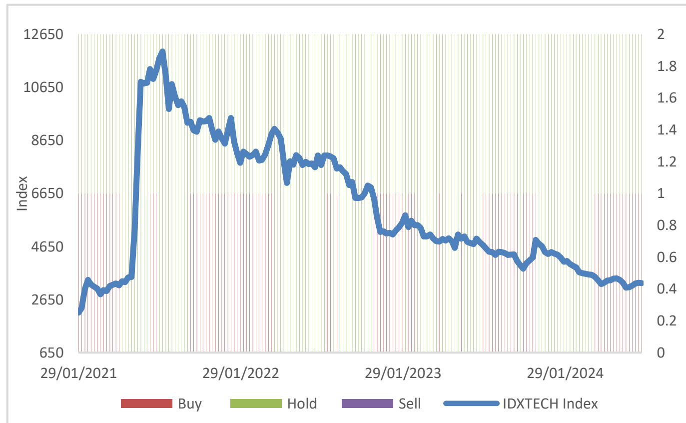
Industrial

Property



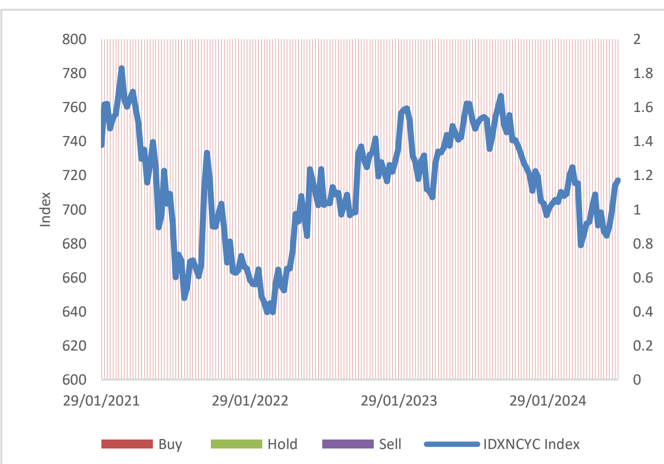
Consumer Cyclical	Technology

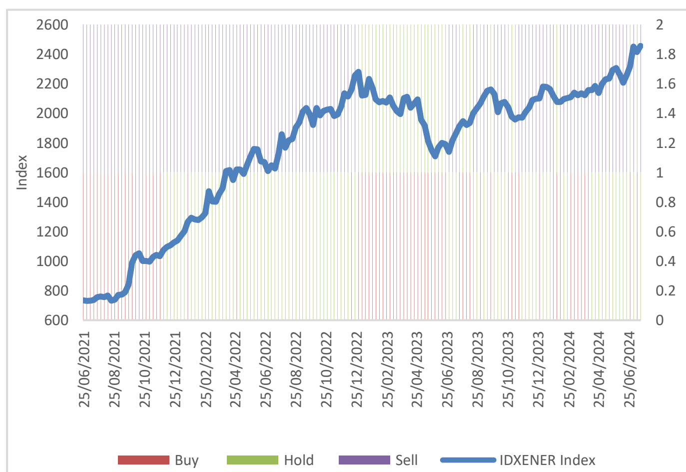




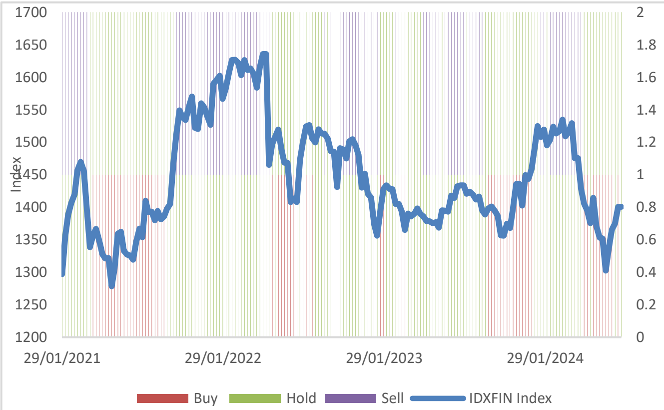
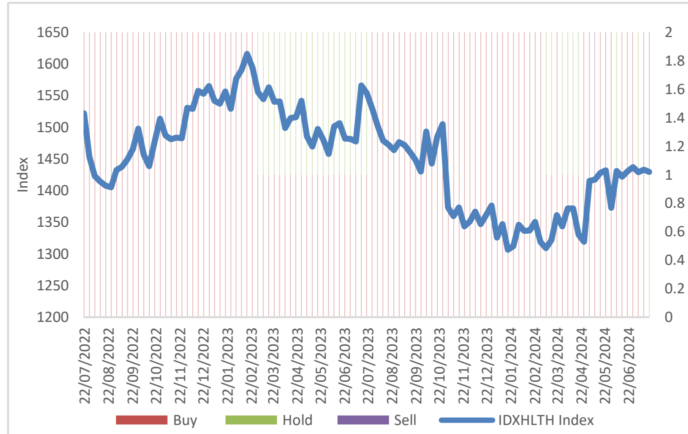
Appendix 2. Table of Sectoral Strategy maximizing Sharp Ratio

Consumer Non-Cyclical	Energy





Financial	Health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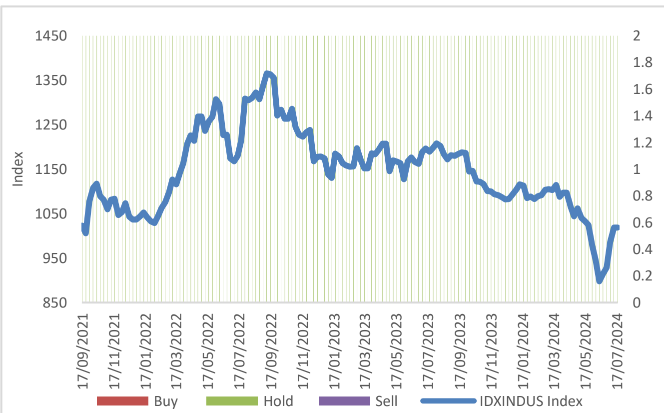
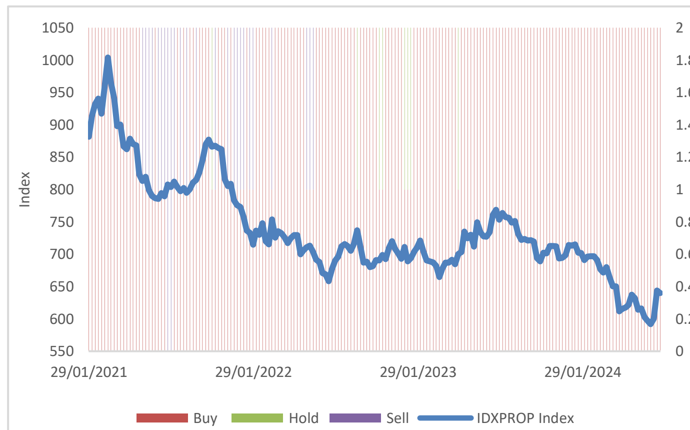
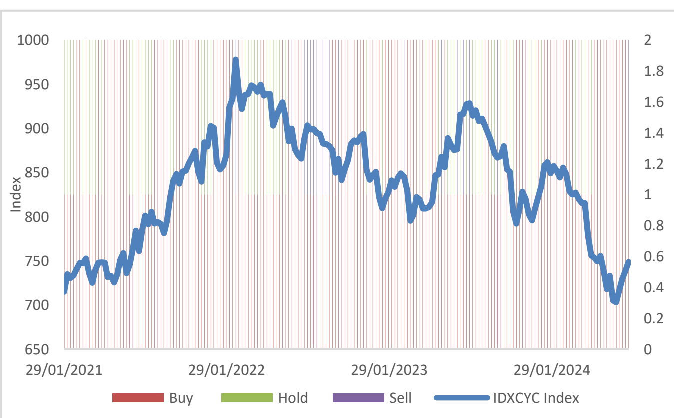
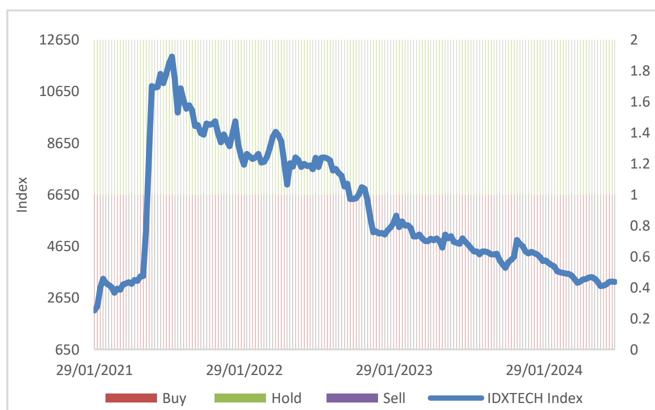
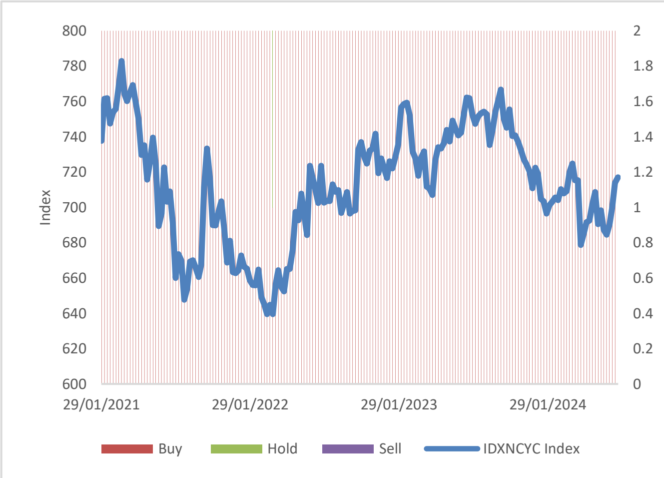
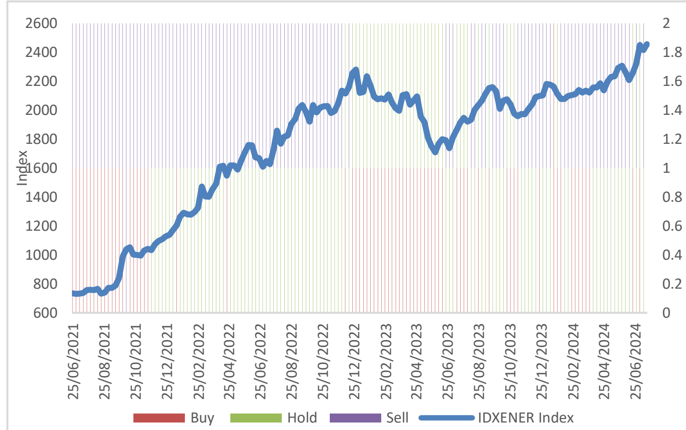
	
Consumer Cyclical	Technology
	

Appendix 3. Table of Sectoral Strategy Minimizing Max Drawdown

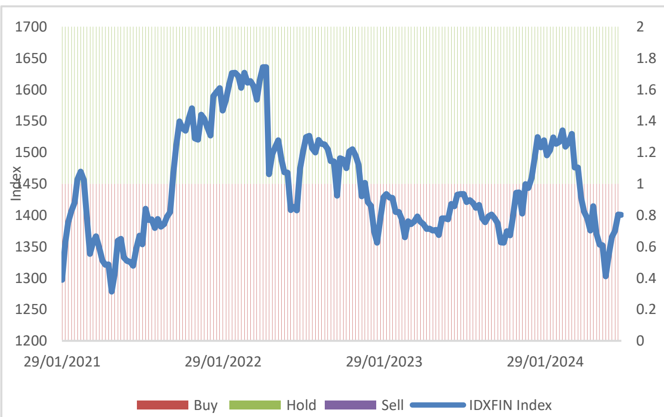
Consumer Non-Cyclical	Energy

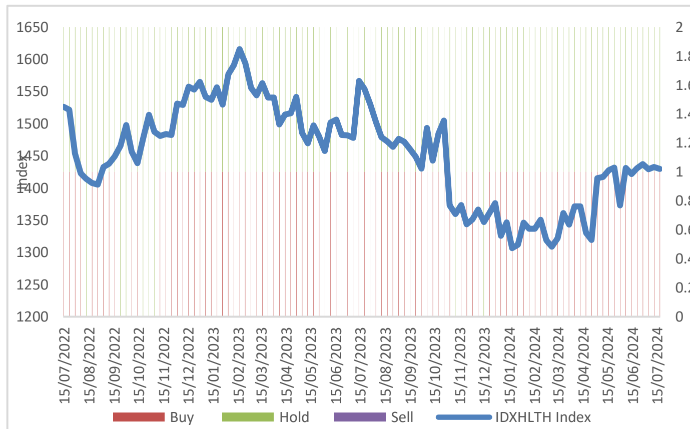




Financial

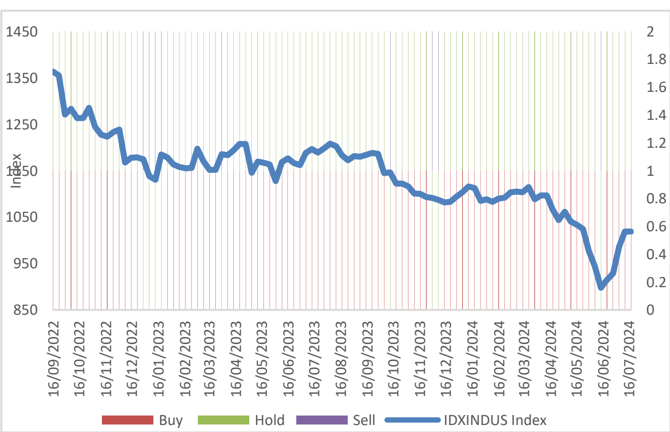
Health

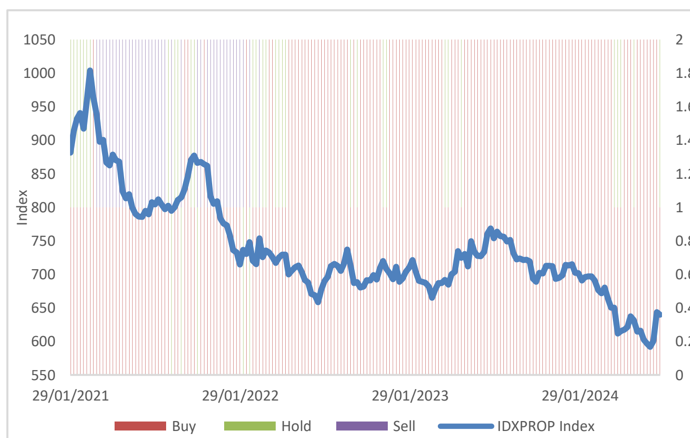




Industrial

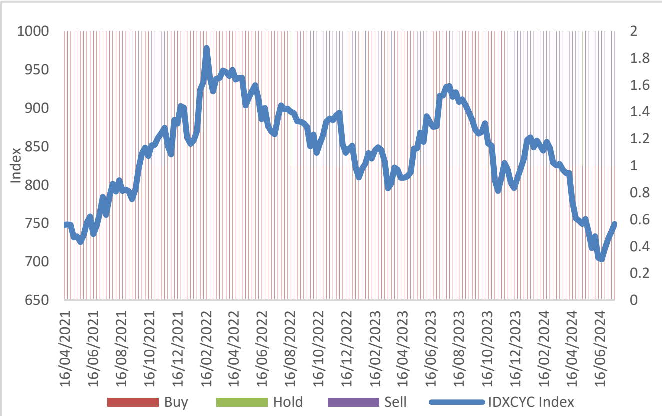
Property

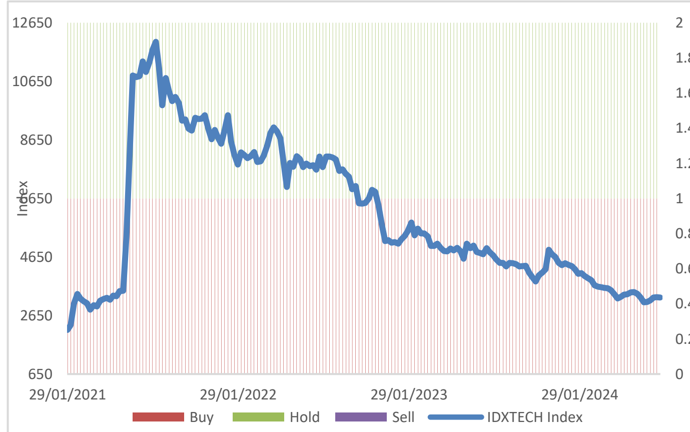




Consumer Cyclical

Technology (Telecommunication)





Appendix 4. Table of Companies Sectoral Strategy Cumulative Return

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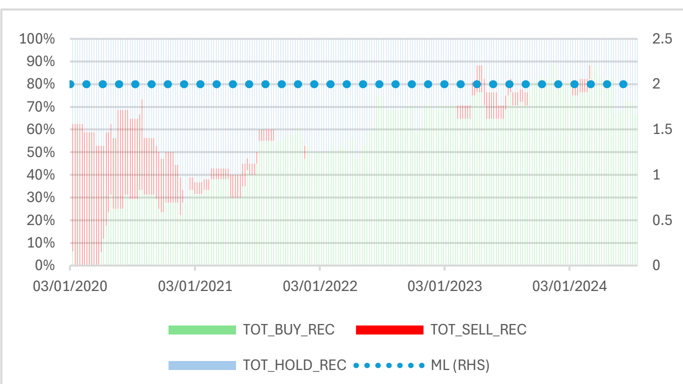

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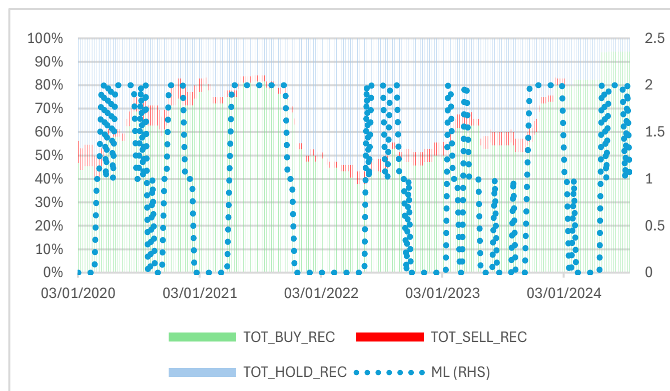

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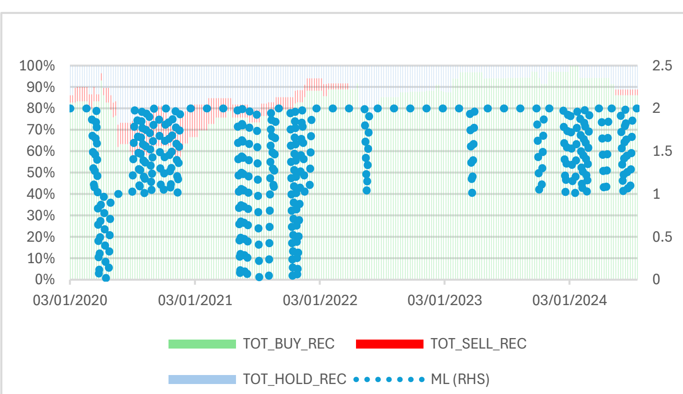

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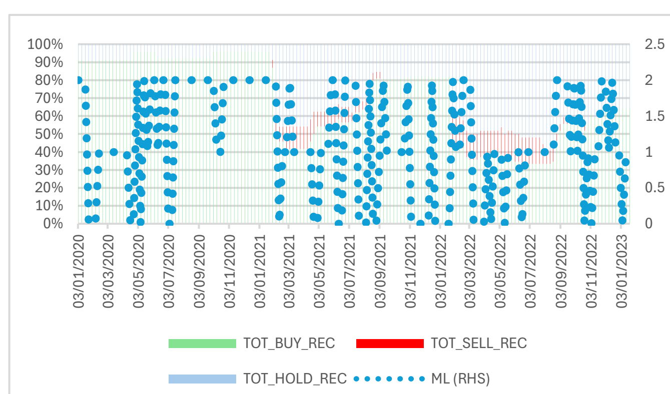
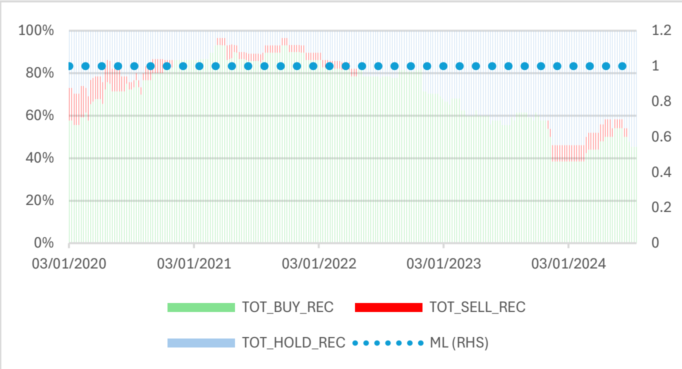


Company in Health

Company in Industrial



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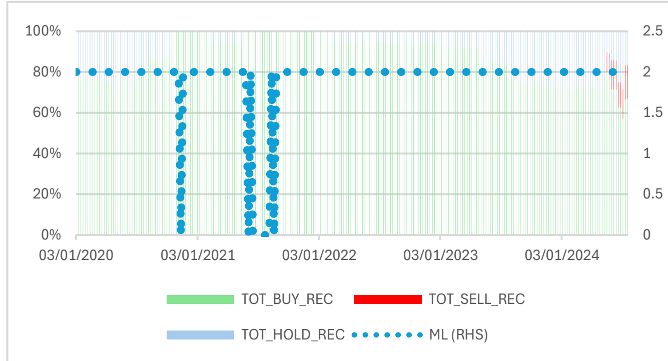
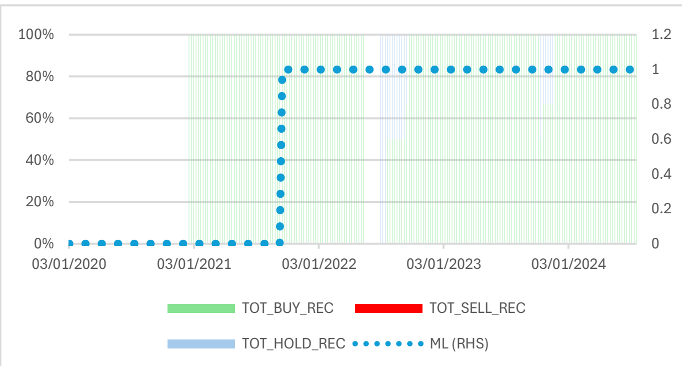


Company in Property



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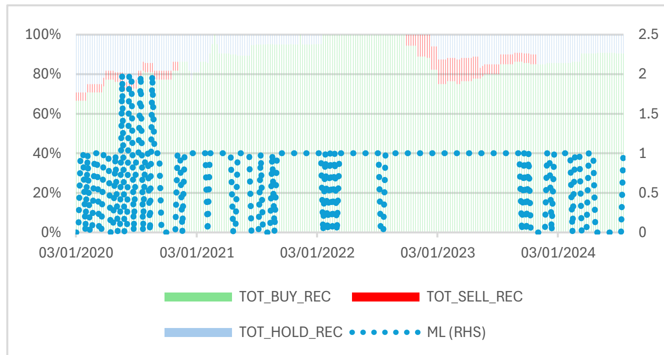

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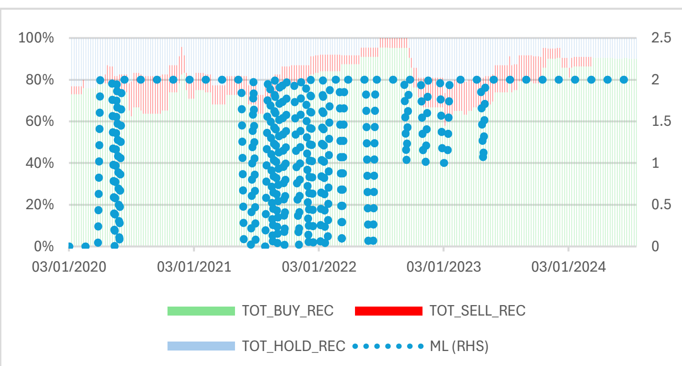

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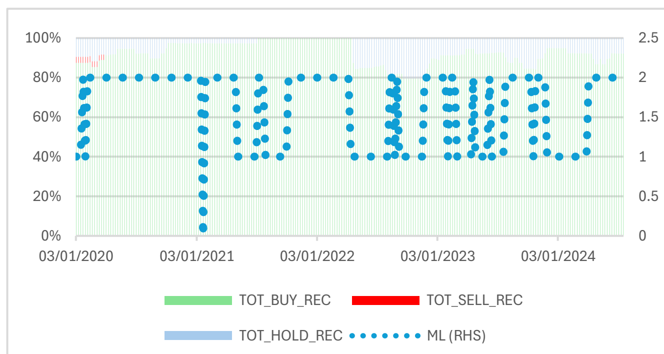
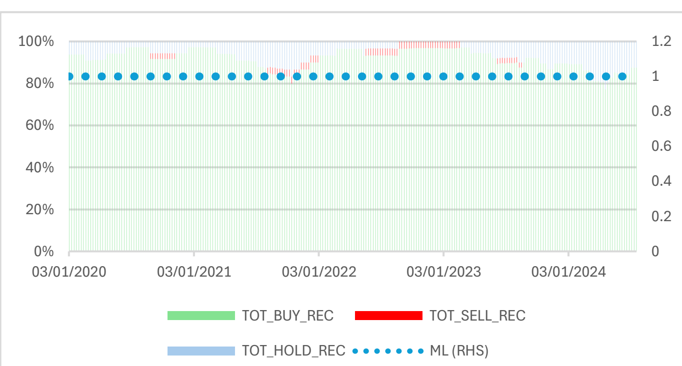
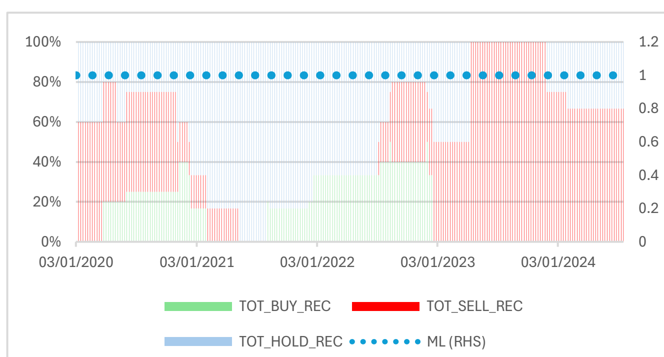


Company in Basic Materials



Company in Consumer Cyclical



Company in Consumer Cyclical

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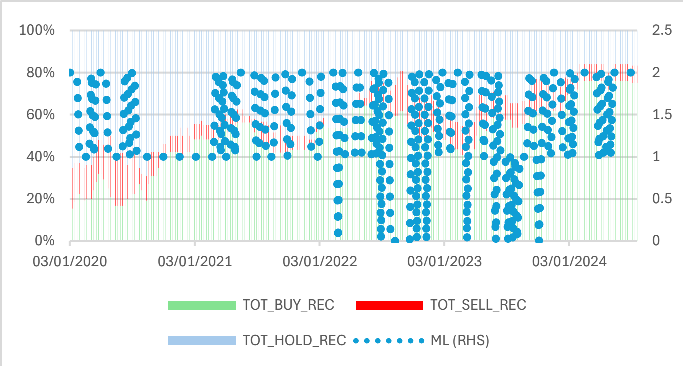
<td>
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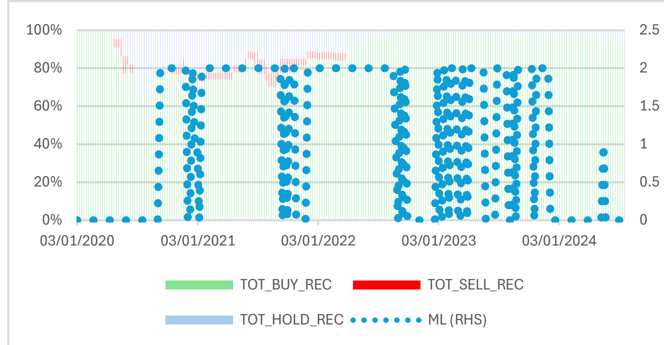
<td>
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Appendix 5. Table of Companies Sectoral Strategy Sharpe Ratio

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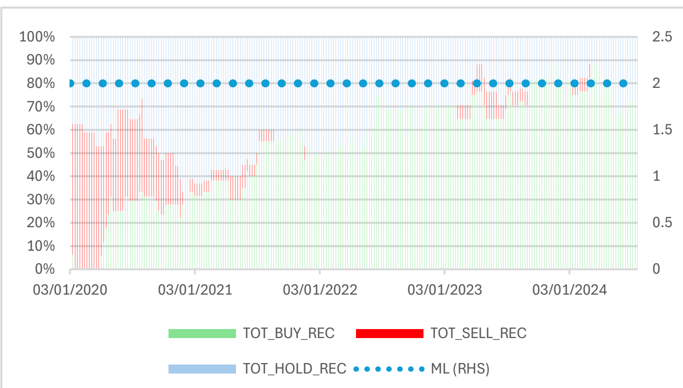
<td>
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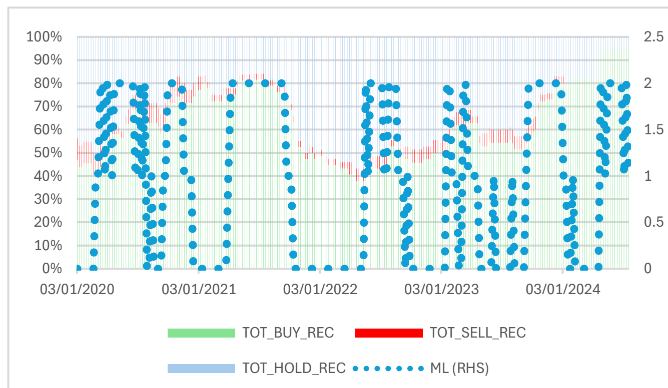
<td>
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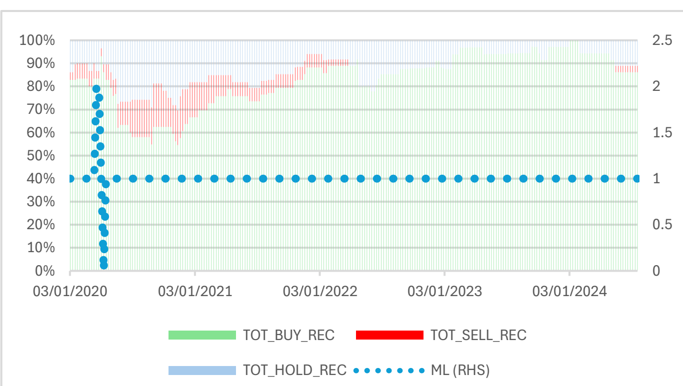
<td>
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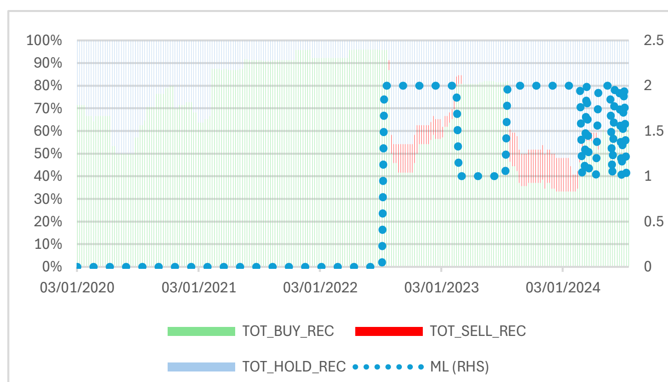
<td>
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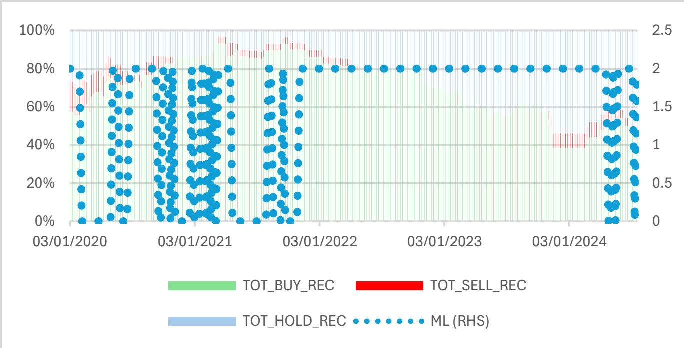
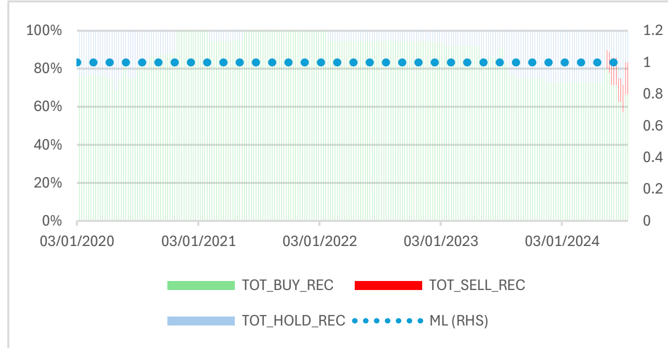
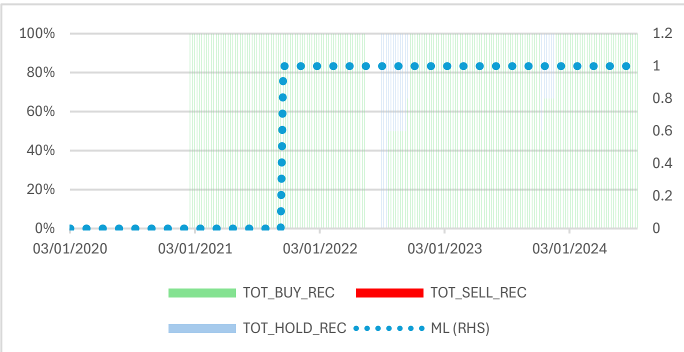
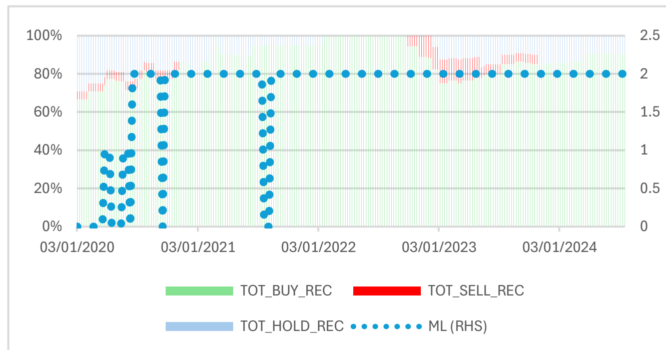




Company in Industrial

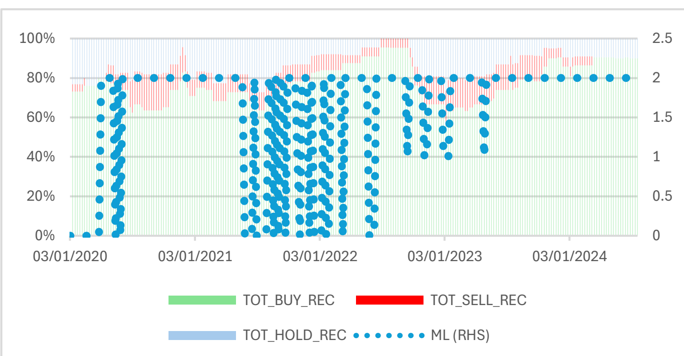
Company in Property

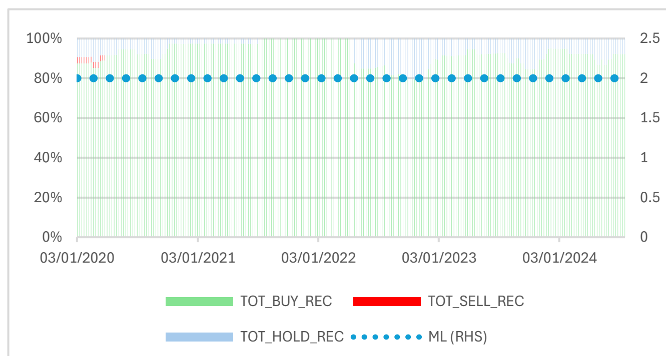




Company in Property

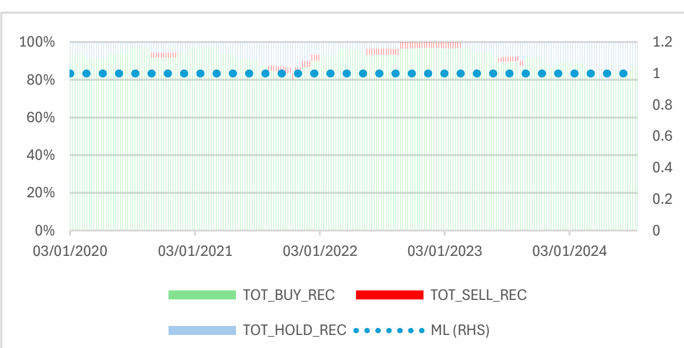
Company in Telecommunication

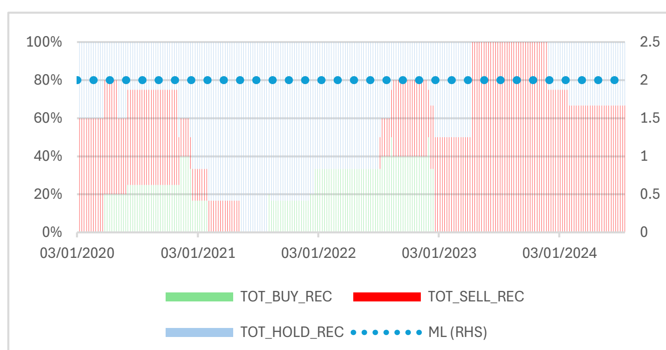




Company in Telecommunication

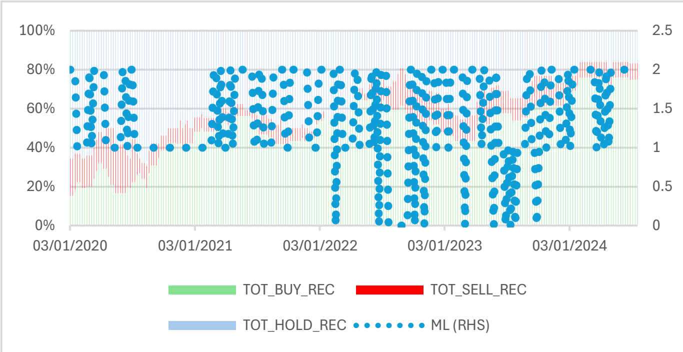
Company in Basic Materials

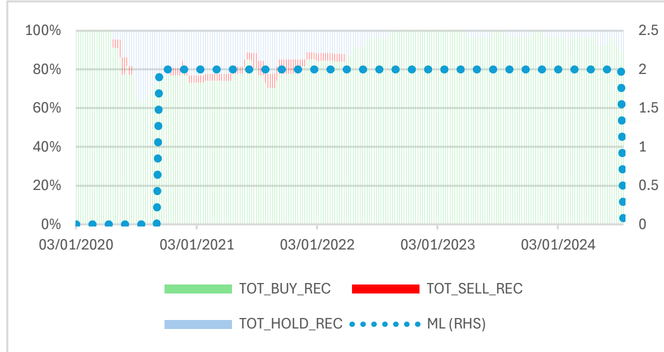




Company in Consumer Cyclical

Company in Consumer Cyclical





Appendix 6. Table of Companies Sectoral Strategy Max Drawdown

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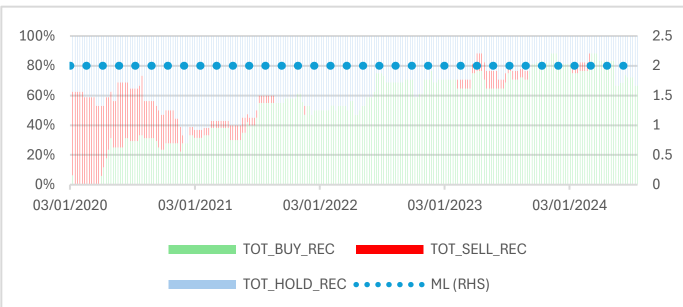
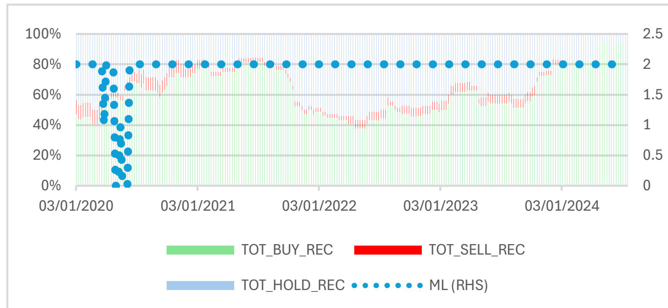
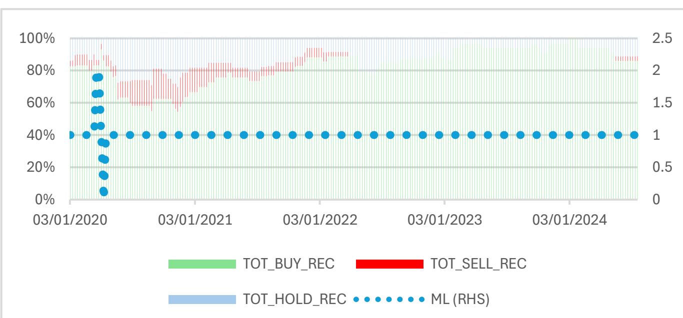
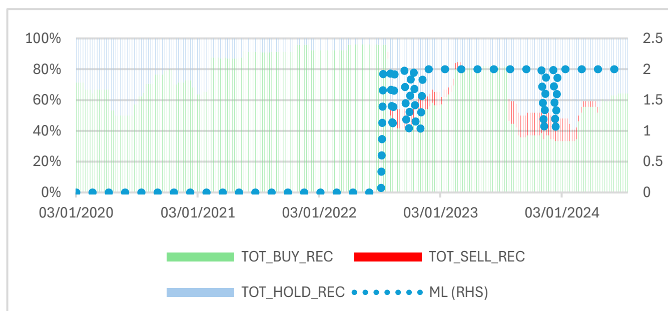


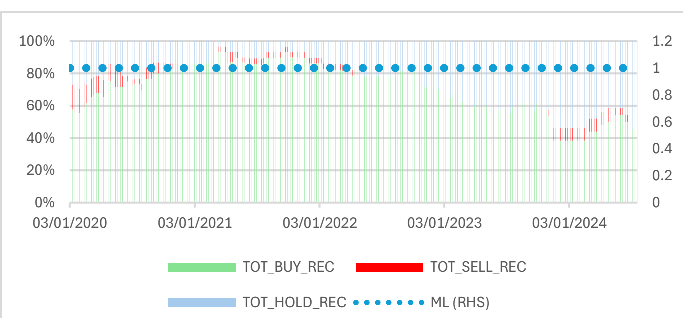


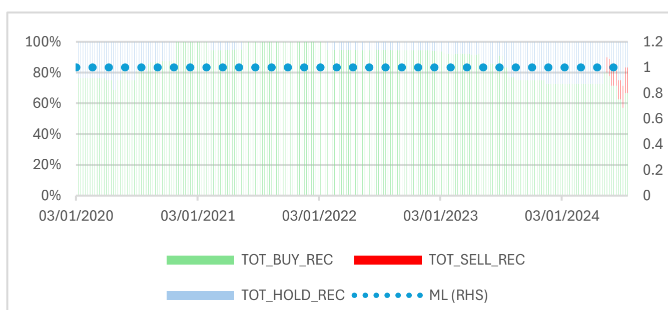
Company in Financial	Company in Health



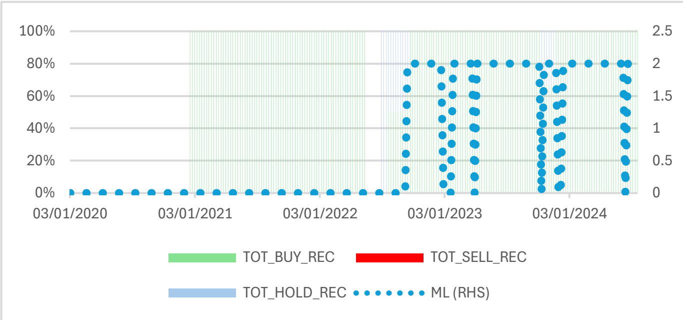


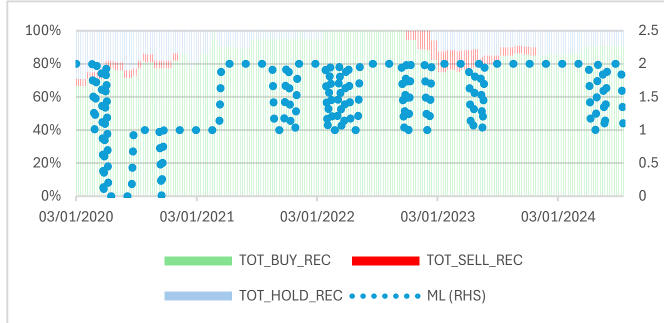
Company in Health	Company in Industrial





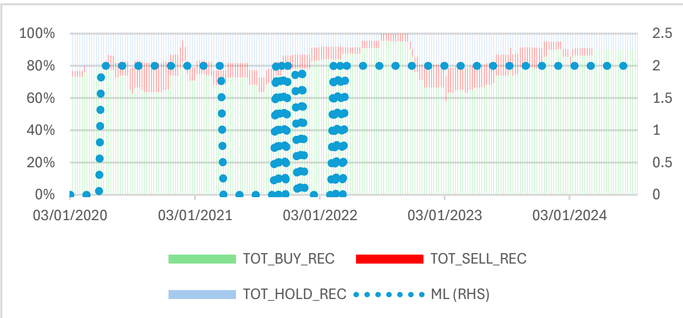
Company in Industrial	Company in Property

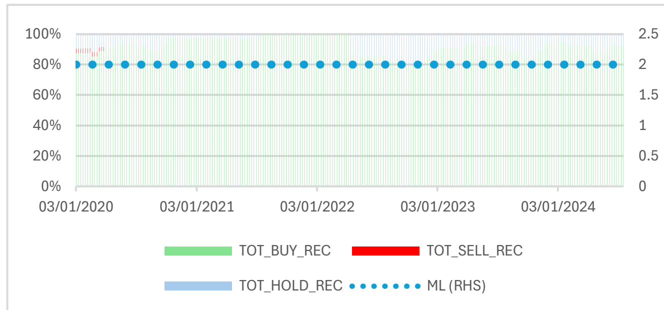




Company in Property

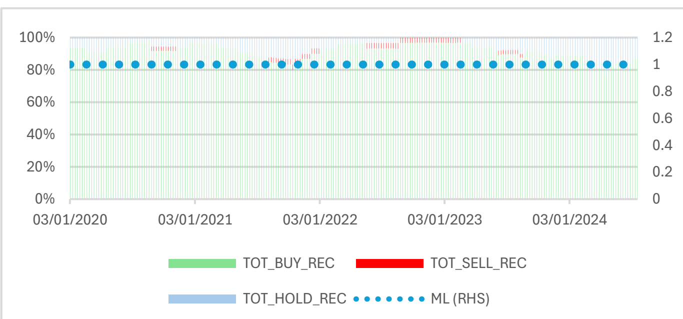
Company in Telecommunication

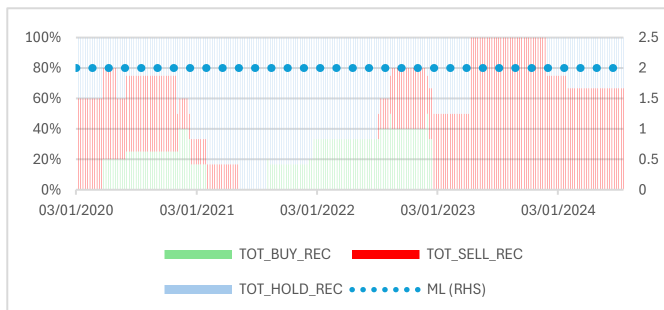




Company in Telecommunication

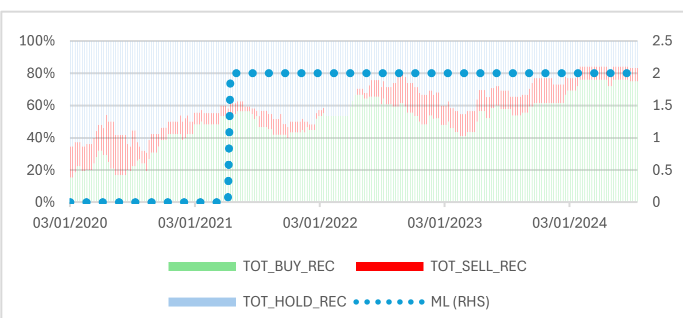
Company in Basic Materials

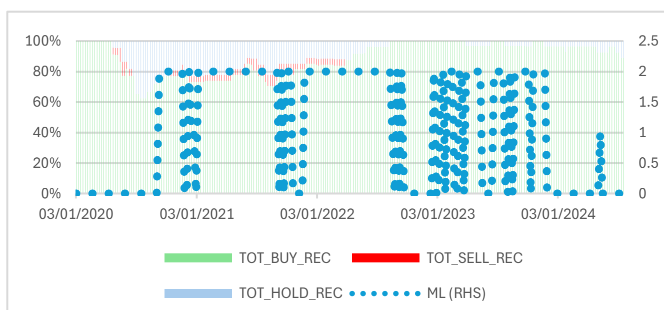




Company in Consumer Cyclical

Company in Consumer Cyclical





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PT. Bahana Pembinaan Usaha Indonesia (Persero)
Gedung Graha CIMB Niaga, 18th Floor
Jl. Jendral Sudirman Kav. 58
RT.5/RW.3, Senayan, Kebayoran Baru
Kota Jakarta Selatan, DKI Jakarta 12190
(+62) 021 2505080
Indonesia Financial Group
PT. Bahana Pembinaan Usaha Indonesia – Persero
@indonesiafinancialgroup
@ifg_id

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