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ADDRESSING CHALLENGES IN STOCK SELECTION: A FINANCIAL DECISION SUPPORT SYSTEM APPROACH

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ABSTRACT – Accurate portfolio selection is a critical aspect of investment management. Traditional stock screeners are commonly used to filter stocks based on key financial metrics. However, the selection process becomes challenging when using price-dependent indicators like the Price to Book ratio and Price to Earnings resulting in either an overwhelming number of options or too few viable choices. To address this challenge, this research paper proposes the design of a Financial Decision Support System (DSS) that combines traditional fundamental analysis with machine learning (ML) to score stock valuations and identify the most undervalued stocks from a large list obtained from stock screeners. Logistic regression and Random Forest models were employed and results were compared for the analysis. 140 stocks and past 10-year data are given as program inputs. When compared to the Logistic Regression model, the Random Forest model fared better with Accuracy, F1-Score, Recall and Precision values of 84.9%, 0.902, 90.0% and 90.4%. The Random forest model when fed with Out of Time Data for the selected list of 140 stocks, 57 stocks scored above 80% and 15 scored above 90% as highly undervalued.

Keywords – Machine Learning (ML); Decision Support System (DSS); Equity Portfolio selection; Stock Intrinsic value; Stock Valuation scoring; Financial Engineering.

JEL Classification codes: G11; G17; G29

1. INTRODUCTION

Significant improvements in stock market investing have been made due to the incorporation of machine learning (ML) techniques. ML algorithms possess the capacity to analyze vast datasets and reveal hidden patterns, thereby transforming portfolio management and optimization practices. By processing historical market data and detecting intricate relationships, ML algorithms offer valuable insights and predictions to investors.

The ability of ML to handle complicated interactions and non-linear connections between stocks and market conditions is a crucial advantage. ML models can capture the complex dynamics of the market, in contrast to traditional models, which frequently assume linear correlations. This results in more accurate predictions and enhanced portfolio profitability. These algorithms are adaptable and may adapt methods in response to fresh information, ensuring that portfolios stay in line with shifting market conditions.

While ML models are beneficial, it is crucial to recognise that human judgement is still necessary and should not be depended upon exclusively. Investors with experience should interpret and follow algorithmic advice. While considering additional factors and drawing upon their own expertise. Moreover, to address potential issues and reduce unexpected outcomes, strong risk management techniques are required.

In conclusion, by utilising vast amounts of data and seeing patterns, the incorporation of ML has revolutionised portfolio selection in stock market investment. Through the synergistic combination of ML and human expertise, investors can improve their performance and get a competitive edge.

1.1 OBJECTIVES OF THIS STUDY ARE AS FOLLOWS:

- To design a Financial Decision Support System (DSS) by combining of traditional fundamental analysis and ML for equity portfolio selection.
- To evaluate the effectiveness of the Logistic regression model in identifying undervalued stocks.
- To assess the performance of the Random Forest model in ranking stocks based on valuation.
- To validate the DSS using out-of-time data for current stock prices.

2. LITERATURE REVIEW

The authors reviewed a collection of work in the field of AI/ML and DSS applied to stock selection. The literature review's main objectives are:

• Examine the current AI/ML selection of a portfolio and stock price forecasting techniques.

• Examine the techniques and models incorporated into the creation of DSS for equity portfolio selection.

• Examine the financial DSS's input parameters for choosing a stock portfolio.

2.1 ML FOR STOCK SELECTION AND PORTFOLIO MANAGEMENT:

Several studies have explored ML algorithms implemented in stock selection and portfolio management. Ref. [1] proposed a hybrid model combining fundamental analysis and ML algorithms, such as Support Vector Machines (SVM), for stock selection. Ref. [2] focused on portfolio selection using SVM models, while [3] examined stock selection based on various ML algorithms. The authors in [4] provided an overview of the applications of ML in stock selection and portfolio management, highlighting the potential of different algorithms. Ref. [5] presented a stock selection model that utilized random forest and fundamental analysis. The effectiveness of ML approaches for stock selection was systematically reviewed by [6]. Wang et al. The use of deep learning models in stock selection was surveyed by [7]. For the purpose of choosing stocks, [8] suggested a hybrid model that integrated financial ratios and ML methods. The authors [9] explored feature engineering techniques for stock selection using ML algorithms. Ref. [10]

conducted a comprehensive analysis of ML techniques in stock price prediction, examining their potential for stock selection.

2.2 Deep Learning based Sentiment Analysis for Stock Selection:

Ref. [11] presented a deep learning framework that utilized financial statements for stock selection based on Deep learning and sentiment analysis in stock selection. A study of deep learning models, like gated recurrent units (GRUs), and long short-term memory (LSTM) networks for stock selection was done by the authors in [12]. Another survey of ML algorithms for stock selection, including deep learning approaches was done in [13]. Ref. [14] conducted a systematic review of ML models for stock selection, outlining their strengths and limitations. An ensemble learning approach that incorporated sentiment analysis for stock selection was proposed by [15].

2.3 Ensemble Learning for Portfolio Selection:

Several studies have explored the application of ensemble learning techniques for portfolio selection. An ensemble portfolio selection method using mixed integer linear programming was proposed in [16]. By combining multiple individual portfolios generated by different models, they aimed to construct an optimized ensemble portfolio. Ref. [17] presented an ensemble portfolio selection model that utilized the comprehensive learning particle swarm optimization algorithm. Their approach integrated the strengths of different individual portfolios to improve overall portfolio performance. Ref. [18] introduced an ensemble learning approach for portfolio selection that considered loss constraints. By leveraging ensemble methods like bagging and boosting, they aimed to construct diversified portfolios that satisfy specific loss constraints. An ensemble learning model for portfolio selection that combined different ML algorithms, such as Decision Trees, Multilayer Perceptron neural network and K-Nearest Neighbors was developed by [19]. Their ensemble model aimed to enhance the accuracy and robustness of portfolio selection. An ensemble portfolio selection approach based on hierarchical clustering and multi-objective optimization was developed by [20]. By leveraging the diversity of individual portfolios generated by different clustering methods and optimizing the ensemble portfolio using multi-objective optimization, they aimed to improve portfolio selection outcomes.

Overall, the above methods seek to improve investment management decision-making by integrating fundamental research, financial ratios, feature engineering, sentiment analysis, and various ML algorithms. These pieces demonstrate the possibilities of ensemble learning strategies for choosing a portfolio. These approaches try to improve portfolio performance, accuracy, and robustness by integrating numerous separate portfolios, using various optimization algorithms, and considering specific constraints.

Key findings from the literature survey:

- Random forest, combined with fundamental analysis, has been found to be effective in stock selection.
- Deep learning models, including LSTM and GRUs, have demonstrated their effectiveness in stock selection.
- Ensemble learning techniques, such as combining individual portfolios and utilizing optimization algorithms, have shown potential for improving portfolio selection.
- Sentiment analysis has been integrated into ensemble learning approaches for stock selection.

3. RESEARCH MODEL AND METHODS

The current model built for DSS for selection of equity portfolio is based on ML classification model Logistic regression. The Design procedure of DSS comprises of following components:

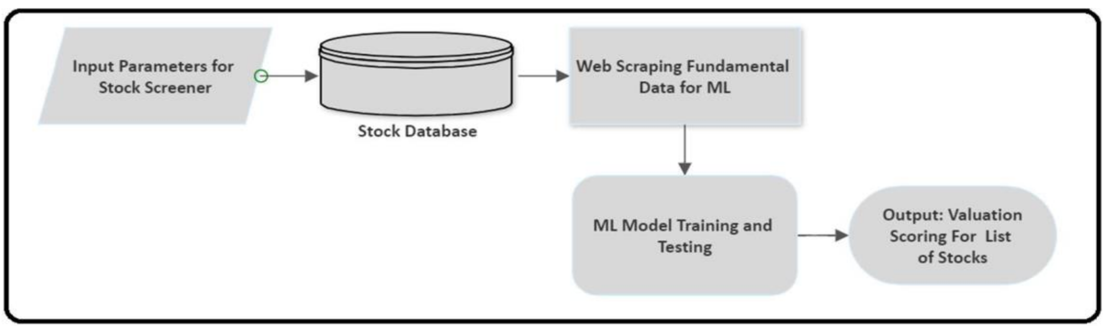

Figure 1: Architecture for ML based Decision Support System

3.1 STEPS FOR DATA COLLECTION ML MODEL TRAINING

To perform data collection and train an ML model, the steps listed below were carried out.:

1. Input Attributes Range Specification:

Define fundamental values like P/E ratio, P/BV ratio, Total Debt/Equity ratio as inputs for the stock screener which are listed in Table 1. The authors considered wide range of price depended attributes P/E and P/BV ratios as price fluctuations occur in short term and in long term it follows stock valuation. For the given inputs the screener filtered 189 indian companies traded in either Bombay stock Exchange (BSE) or National Stock Exchange (NSE).

2. Data Collection:

A Python web scraping code programmed to collect past 10 years historical data for the 189 screened companies, ensuring compliance with website scraping policies. Historical data collected with the attribute listed in Table 2.

3. Data Processing:

The extracted data is processed to address missing values, duplicates, and adjustments required due to corporate actions (e.g., stock splits, bonuses). Out of 189 only 140 companies are listed for more than 10 years in BSE or NSE.

4. **Processing Data for ML model training:**

Further processing the data by removing outliers and formatting it for ML algorithms. Data split into 70-30 training - testing datasets, resulted in 1196 instances after removing outliers.

5. Model Building:

A top-down approach is adopted for model building, employing Recursive Feature Elimination and Variance Inflation Factor techniques to systematically eliminate features and identify the most relevant feature for stock portfolio selection.

6. Hyper-Pparameters Tuning:

To maximise a model's performance in ML, hyperparameter tuning is a crucial step. Hyperparameter tuning involves identification of the optimal values of parameters that define the performance of the ML model.

7. Model Evaluation:

The final model is tested using the reserved testing dataset. Performance metrics are calculated and compared between the train and test datasets to assess the model's effectiveness.
By following this architecture, the Financial DSS facilitates selection of stock portfolios, integrating web scraping, data processing, feature selection and ML model building.

TABLE 1: Attributes for inputs for stock screener

The Inputs for stock screener:	Min.	Max.
• P/E Ratio	0	40
• Price to Tangible Book	0	3
• Net Profit Margin	4	Max.
• Current Ratio	1.25	Max.
• Total Debt to Equity	0	1.5

3.2 STOCK VALUATION MODEL:

For the current study Modified Grahams' Intrinsic value formula [21] was used for stock valuation. The Risk free rate of return 'r' is obtained from RBI website [22]. 6.5 at the time of collection. and Long duration AAA Bond yield obtained from NSE [23] 7.54 at the time of collection.

$$\text{IntrinsicValue} = \frac{\text{EPSx}(7+\text{g})\text{x}(\text{r})}{\text{Y}}$$

Where:
EPS – is the Annualized Per Share Earnings.
'7' - PE ratio of a stock at 0% growth rate.
'g' – Expected Earnings growth rate (assumed from the past 10 year Avg. Annual Growth Rate of the stock EPS).
'r' - Risk free rate of return. (Term Deposit Rate >1 Year).
'Y' - NIFTY AAA Long duration Bond yield.

3.2 LOGISTIC REGRESSION MODEL:

Logistic regression is a binary classification algorithm, such as determining if a stock is undervalued or not. A linear equation's result can be converted using the sigmoid function into a probability value between 0 and 1.. The model is trained using optimization algorithms to find the best parameters that minimize a cost function. A decision boundary is used to classify instances based on a threshold (usually 0.5). Logistic regression is evaluated using metrics like accuracy, precision, recall, and F1 score.

$$\ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots + \beta_n X_n$$

Where:
P – Probability of dependent variable.
'β_0' - Constant
'β_i' – Coefficient of i^{th} Feature.
'X_i' – i^{th} Feature value.
'n' – Total number of Features

3.3 RANDOM FOREST MODEL:

Random Forest combines numarous decision trees for classification, it is an ensemble learning algorithm. It uses bagging to create subsets of the training data and random feature selection at each node. Predictions are made through majority voting. Random Forest also provides importance of features. It is known for its robustness and is widely used in different domains.

Entropy is a measure of impurity or disorder in a node of a decision tree. It calculates the average amount of information needed to classify an element in the node. The formula for entropy is:

$$\text{Entropy} = -\sum_{i=1}^{n} P_i \cdot \log_2(P_i)$$

Where:
P_i is the proportion of samples in the subset belonging to class i.

Table 2: Features collected from Historical data

S. No	Variable Name	Description	Data Type
1	Basic EPS (Rs.)	Basic per share annualised earnings of a company	Integer
2	Net Profit Margin (%)	Percentage of Net profit in Total Revenue	Float
3	Book Value (Rs.)	Net value of a company's assets minus its liabilities	Integer
4	Price/BV	Market price per book value of a company's common stock	Float
5	Current Ratio	Ratio of Current Assets to Current Liabilities	Float
6	Dividend / Share (Rs.)	Paid out portion of a company's earnings	Integer
7	Dividend Yield (%)	Annual dividend of a stock as a percentage of its current market price.	Integer
8	Total Debt/Equity	Proportion of a company's total debt relative to its shareholders' equity	Float
9	Asset Turnover Ratio (%)	Percentage of Net Sales to Total Average Assets	Float
10	Inventory Turnover Ratio	Cost of goods sold by the Average Inventory	Float
11	Return on Assets (%)	Percentage of Net Income to Total Average Assets	Float
12	EPS Growth Rate	Annual Earnings growth rate	Integer
13	BV Growth Rate	Annual Book Value growth rate	Integer
14	Historic Price	Past prices of a company’s stock over a specific time.	Integer
15	Undervalued (Target)	‘1’ for undervalued stock, ‘0’ for Over or Fairly valued stock	Boolean

4. METHODOLOGY

The general steps involve in ML model training are preparing and preprocessing the data, selecting relevant features, training the model, evaluating its performance, hyperparameter tuning, and making predictions. Final model is fit to the test dataset. Following section explains the steps followed for Logistic Regression and Random Forest Models.

4.1 Logistic Regression Model:

After processing data, Splitting the Data into Train Test datasets in 70-30 ratio, relevant features are selected by using Variance Inflation Factor and Recursive feature Elimination. The model is Fit to the Train Dataset and Tested on the Test dataset. After testing on test dataset model and evaluating its performance, predictions are made. Logistic regression assumes a linear relationship between features and the logarithm of the odds of the target variable. Final Logistic Regression model is fit to the test dataset. The final model's Receiver Operating Characteristic (ROC) curve shown in Figure 2 has the area under curve of 88%. The ROC curve evaluates the trade-off between true positive rate (TPR or sensitivity) and false positive rate (FPR) across the classification thresholds. Figure 3 shows the Precision-Recall graph used to classify a stock as Undervalued or Not depending on probability. Here the cut-off is taken as 0.63.

The final model is having only 10 most significant features of the total 14 initially selected Table 3 shows the final model with the feature coefficient or significance.

TABLE 3: Significant Features List for Final Model

Features	Coef. Value	Coef. No.	Variance Inflaton Factor
Total Debt/Equity	2.51	β_6	1.09
EPS Growth Rate	0.53	β_8	1.15
Dividend_Yield	0.24	β_5	1.58
Constant	0.18	β_0	-
Return on Assets (%)	0.18	β_7	3.82
Basic EPS (Rs.)	0.14	β_1	3.44
Book Value /Share (Rs.)	0	β_2	2.44
Historic Price	-0.01	β_9	1.83
Dividend / Share(Rs.)	-0.13	β_4	3.12
Price/BV	-0.58	β_3	2.99

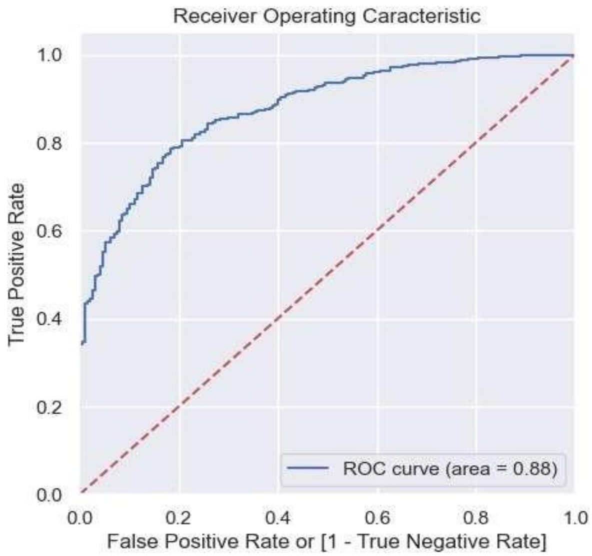

Figure 2: ROC curve Logistic Regression Model

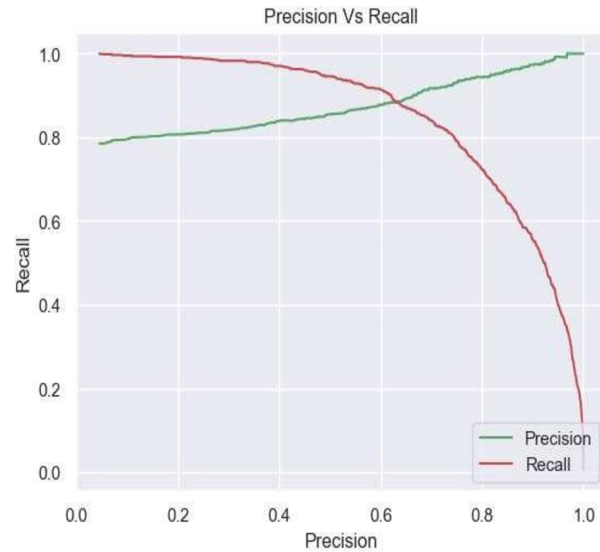

Figure 3: Precision – Recall Trade-off

4.2 Random Forest Model:

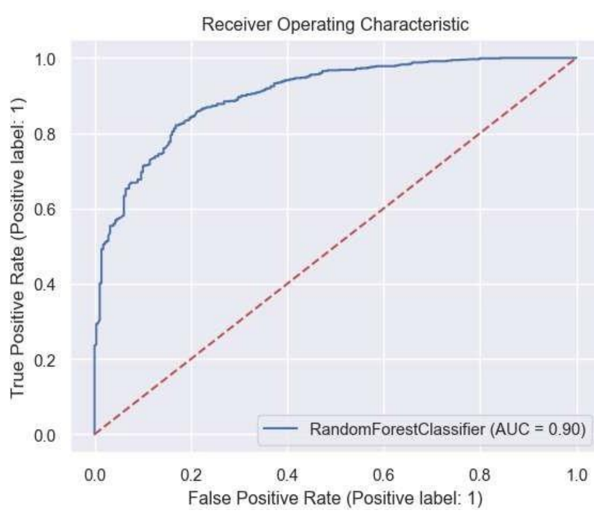

Figure 4: ROC curve Random Forest Model

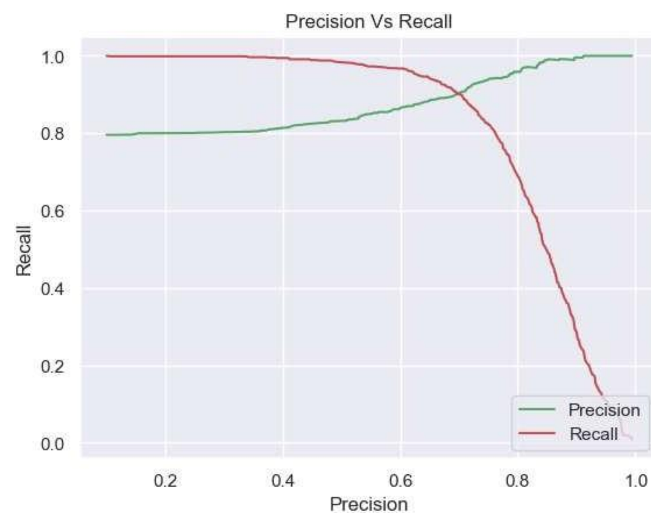

Figure 5: Precision - Recall Trade-off Graph

Random Forest model, create subsets of the training data and randomly selects features at each node. Predictions are made through majority voting. The initial model is optimized by tuning hyperparameters, and making predictions. Final Random Forest model is derived at Max. Tree depth 5, Min. Samples leaf 10, no. of estimators 5 as the best model after hyperparameter tuning. The final model's ROC curve shown in Figure 4 has the area under curve of 90%.

5.RESULTS

5.1 LINEAR REGRESSION MODEL

From the Precision-Recall trade-off graph shown in Figure 3, the cutoff probability for classifying as 'Undervalued' is set at 0.63. The cutoff value proves useful in striking a balance between False Positive and True Negative values. For more conservative investors, raising the cutoff value can reduce False Positives. Table 4 presents the Accuracy, F1 Score, Precision, and Recall values.

The Performance metrics are calculated and compared. In situations where the consequences of false-positive classifications are more severe than false-negative classifications, such as in this scenario where misclassifying an overvalued stock as undervalued can result in investor losses, it may be advisable to increase the classification probability. The optimal cutoff, however, is determined based on the Precision-Recall graph depicted in Figure 3.

Table 4: Performance Evaluation Metrics Logistic Regression Model

Performance Metrics	Train Data Set	Test Data Set
Accuracy	80.53%	78.55%
F1 score	0.867	0.857
Recall	0.818	0.852
Precision	0.922	0.861

5.2 RANDOM FOREST MODEL

Based on the Precision-Recall trade-off graph displayed in Figure 5, the chosen cutoff probability for classifying as 'Undervalued' is 0.73. Conservative investors can increasing the cutoff value to mitigate False Positives. Table 5 provides a comprehensive overview of the Performance Evaluation Metrics, encompassing the Out of Bag Score, Accuracy, F1 Score, Precision, and Recall values.

The Performance metrics are calculated to evaluate the model's efficacy on unseen data, utilizing the Out of Bag Score. While the accuracy of the model is typically employed as a measure of performance for unbiased classification probabilities, it may be prudent to adjust the classification probability in cases where false-positive classifications carry more significant consequences than false-negative classifications. This situation is exemplified in the context of misclassifying an overvalued stock as undervalued, potentially resulting in financial losses for investors. Therefore, the optimal cutoff is determined based on the Precision-Recall graph depicted in Figure 5.

Table 5: Performance Evaluation Metrics Random Forest Model

Performance Metrics	Train Data Set
Out of Bag Score	0.812
Accuracy	84.9%
F1 score	0.902
Recall	90.0%
Precision	90.4%

5.3 RANDOM FOREST MODEL PERFORMANCE ON OUT OF TIME DATA

The random forest model is fit to Out of time data of 140 stocks at current stock price. The Random Forest model output shows that 57 stocks scored above 80% out of which 15 stocks scored above 90%, indicating that they were highly undervalued. The resulting list of stocks that are highly undervalued are relative fewer in number compare to the 140. Thus helping the investors in portfolio selection.

6. CONCLUSIONS:

In conclusion, this study holds significant implications for investors and decision support when it comes to categorizing selected companies as undervalued or overvalued based on intrinsic value. The main findings can be summarized as follows:

1. Importance of Hybrid DSS: The integration of machine learning techniques and intrinsic value assessment within a hybrid Decision Support System (DSS) aids in the process of stock selection. It allows for the swift identification of the most undervalued stocks from a given list, providing valuable insights to inform investment decisions.

2. Determining Valuation Scores: The DSS assists investors by generating valuation scores for the stocks they hold. These scores serve as a guide for selling stocks with lower valuation scores and acquiring stocks with higher valuation scores, enabling a more informed approach to managing investment portfolios.

3. Resilience during Market Crashes: The Financial DSS proves particularly beneficial during periods of market crashes or corrections. Unlike traditional regression models that heavily rely on historical price data for predicting future prices, the current model aids individual investors in identifying the most undervalued stocks from a large pool of discounted stocks. This capability

helps mitigate potential losses and maximize opportunities, even in situations where market behavior deviates from the norm.

Overall, the incorporation of machine learning techniques and intrinsic value assessment into the Decision Support System empowers investors to make well-informed decisions, capitalize on undervalued stocks, and navigate through market fluctuations more effectively. This approach provides a valuable tool for investors and decision-makers in the financial realm.

FUTURE SCOPE OF STUDY:

1. Evaluation of Model Robustness: Assessing the robustness of the model by conducting sensitivity analyses and stress tests would enhance its reliability. Future studies could explore how the model performs under different scenarios, market conditions, and economic cycles to validate its effectiveness and identify any potential limitations.

2. Integration of Risk Assessment: Incorporating risk assessment metrics and techniques into the valuation model would provide a more comprehensive framework for investment decision-making. Future research could explore the integration of risk factors, such as volatility, market liquidity, or credit risk.

3. Expansion to Different Markets: The current study focused on a specific market or set of stocks. Future research could explore the application of the model to different markets, such as international markets or specific sectors, to assess its effectiveness and adaptability across diverse investment landscapes.

These future research directions would contribute to the ongoing development and refinement of the valuation model, leading to more robust and comprehensive approaches for stock selection and investment decision-making.

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