Predicting Dividend Statuses of Thai Listed Companies Using Machine Learning

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Abstract
This study addresses the dividend puzzle by utilizing machine learning techniques to forecast dividend status of 515 non-financial companies listed on the Stock Exchange of Thailand (SET). By using random forest, boosted tree, and decision tree models, we classified dividend status into 4 categories: grow, maintain, decline, and remain unpaid. The results indicate that the boosted tree method provided superior predictive power compared to the random forest and decision tree methods. Predicting dividend policy in emerging markets is valuable for investors and analysts to understand future dividend prospects, which is a critical signal of a company's financial well-being.

Keywords: Machine learning, dividends, forecasting, prediction

Introduction
The prediction of dividend policy is one of the challenging issues in financial economics which we often refer to as the dividend puzzle. Dividends are a critical signal to investors for a company's future prospects and wellbeing. While the traditional financial models have relied on linear models and payout ratios to forecast dividend status, recent developments in machine learning shifts this focus towards forecasting using non-linear structures. These non-linear methods have proven more effective than traditional financial methods due to their ability to use many variables for forecasting which helps them model much more complex relationships. Recent literature has emphasized ML model's outperformance of traditional models in forecasting financial behavior (Wang et al., 2024; Ivașcu, 2024; McMillan & Wohar, 2010). Random forest, XG, and LASSO models provide superior accuracy for complex financial behavior such as dividend growth which may follow non-linear patterns.

To ensure high forecasting accuracy of dividend status, many papers use a wide range of financial determinants. Key variables often include ROE, ROA, inflation, profitability, and firm size.

This paper focuses on the Stock Exchange of Thailand (SET), analyzing 515 non-financial firms over the time period of 2000-2024 by transforming raw financial statement data into 223 quantitative features. This study classifies dividend status into 4 different categories: grow, decline, maintain, and remain unpaid. By applying random forest, boosted tree, decision tree models, this paper aims to provide a robust forecasting model for understanding dividend status in an emerging market context.

The results emphasized that boosted tree models outperformed the random forest and decision tree models.

While many studies in the literature have used ML methods in developed markets, this study is expected to contribute to the literature by applying ML techniques to Thailand as an emerging market. This paper hopes to bridge the gap between advanced ML techniques and the emerging market dividend policy.

This paper proceeds as follows: section 2 provides background information on the existing literature, section 3 highlights the empirical findings, and section 4 concludes the paper.

Literature Review

Various methodologies have been used to forecast dividends such as machine learning (Bhat, 2022; Wang et al., 2024; Raju et al., 2023; Diez et al., 2025), logistic regression model (Kumar and Sinha, 2024; Chen, 2009; Lee and Mason, 2010; Álvarez-Díez et al., 2024), LASSO (Elyasiani et al., 2019; Vodwal and Negi, 2023), Fixed Effect Panel Regression (Dewasiri et al., 2019), Random Forest (Ivașcu, 2024), VAR (Engsted and Pedersen, 2010), ESTR (McMillan and Wohar, 2010), STAR (Jawadi, 2009), Lintner's partial-adjustment model (Brown et al., 2008), GA/ANN (Konak et al., 2024; Won et al., 2012), SVM models (Bae, 2010).

The variables as the determinant of dividends used in the literature often varied such as firm size (Álvarez-Díez et al., 2024), total polarity (Diez et al., 2025), stock price (Bae, 2010; Won et al., 2012), Tobin's Q (Vodwal & Negi, 2023), aggregate dividend index (Konak et al., 2024), capital market structure index (Brown et al., 2008), time series index of dividends (Jawadi, 2009), price to dividend ratio (McMillan & Wohar, 2010), per capita household income (Lee & Mason, 2007), real and nominal returns (Engsted & Pedersen, 2010), ROA (Chen, 2009), ROCE (Raju et al., 2023), EPS (Wang et al., 2024), Debt to Equity (Ivașcu, 2024), free cash flow (Dewasiri et al., 2019), taxes (Elyasiani et al., 2019), beta (Kumar & Sinha, 2024), and financial risk (Bhat, 2022).

Many studies have focused on various countries and regions such as India (Bhat, 2022; Kumar & Sinha, 2024; Raju et al., 2023; Vodwal & Negi, 2023), USA (Wang et al. 2024; Chen, 2009; Engsted & Peterson, 2010), South Korea (Bae, 2010; Won et al., 2012), Iran (Elyasiani et al., 2019), Sri Lanka (Dewasiri et al., 2019), Taiwan (Lee & Mason, 2007), Turkey (Konak et al., 2024), G7 Countries (Jawadi, 2009; McMillan and Wohar, 2010), Denmark (Engsted & Pedersen, 2010), Sweden (Engsted & Pedersen, 2010), UK (Engsted & Pedersen, 2010), global (Ivașcu, 2024; Brown et al., 2008).

The empirical findings suggest and emphasize that machine learning models perform better at predicting dividends than traditional methods of prediction. For example, Wang et al. (2024) found that machine learning models used for dividend forecasting are more accurate than traditional analysis based and payout-ratio based methods, particularly for complex firms. Similarly, Ivașcu (2024) found that modern methods such as Random Forest and XGBoost outperform more traditional methods such as Decision Tree and Logistic Regression models.

All the many studies focus on machine learning-based models but other studies such as those from McMillan & Wohar (2010) and Jawadi (2009) emphasize the importance of non-linearity in dividend behavior. The nature of dividend behavior has fluctuated over time, and the effect of time based change in dividends is much more important than model selection (Chen, 2009).

The predictability of dividends also varies based on region. For example, Engsted & Peterson (2010) found that dividend growth predictability shifts based on if they used nominal vs. real data in the US and EU market. The US market was mainly affected by inflation, showing different patterns than those of EU markets.

Recent studies also integrate alternative indicators of dividend predictability. For example, Álvarez-Díez et al. (2024) found that using sentiment analysis as an indicator predicted short-term abnormal returns and that negative news offered profitable trading opportunities. Similarly, Diez et al. (2025) used ChatGPT-extracted news sentiment to predict returns after dividend announcements which aids in short-term trading. These results, however, need further validation.

Table 1. An extensive review of literature

Author	**Year**	**Key variables**	**Method**	**Key findings**	**Region**	**Time Period**
Bhat	2022	Dividends, size, liquidity, financial risk	ML	The ANN-MLP model achieved the most predictive accuracy at 82.36%.	India	2013 - 2018
Kumar & Sinha	2024	EPS, NS, CR, BETA, ROA	Logit regression	The dividend prediction model using the random forest algorithm achieved the highest prediction accuracy of 90.77% and 77.31%.	India	2006 - 2022
Elyasiani et al.	2019	Tax, DPS, LEV, Age, Liquidity	LASSO	LASSO-selected variables can improve in-sample and out-of-sample	Iran	2009 - 2016

				prediction power of dividend payout ratio.		
Dewasiri et al.	2019	Corporate Governance, Free Cash Flow, Life Cycle of the Firm	Binary Logistic Regression, panel data	Past dividend decision is a common determinant with implications for both inclination to pay dividends and its payouts.	Sri Lanka	2010 - 2016
Ivașcu	2024	Debt to Equity, Price to Sales, ROE, Price to Book	ML and PCA	Random Forest and XGBoost outperform the popular Decision Tree and Logistic regression models.	Global	End of 2020
Wang et al.	2024	EPS, DPS	MSE Framework	Machine-learning dividend forecasts are more accurate than traditional analyst-based and payout-ratio-based methods.	USA	2005 - 2021
Raju et al.	2023	ROCE, QoQ Profit Growth, YoY Profit Growth, Cash flow generation	AI/ML	AI/ML-based fundamental, technical, and sentiment analysis into a three-dimensional model can select an Indian stock portfolio that outperforms a NIFTY 50 index fund.	India	2023
Chen	2009	Real GDP growth,	Regression	Before WWII, dividend yields	USA	1872 - 2005

		dividend growth, ROA, equity return		predicted dividend growth; after WWII, they predicted returns instead.		
Engsted & Pedersen	2010	Dividend-price ratio, real and nominal return, inflation, innovation to returns	VAR	Return and dividend growth predictability shifts when using real vs. nominal data, mainly due to US inflation effects. European markets show different patterns.	USA, Denmark, Sweden, UK	1926 - 2008
Lee & Mason	2007	Age, dividends, wages, per capita household income	Regression	Income depends more on the overall population age structure than on family age, and the main winners from the demographic dividend were the first low-fertility generation.	Taiwan	1978 - 1998
McMillan & Wohar	2010	Price to Dividend Ratio	ESTR	The asymmetric non-linear model predicts returns better than the linear one.	G7	1974 - 2007
Jawadi	2009	Dividends	STAR	STAR models capture non-linear dynamics and forecast dividends better than linear models in most countries.	G7	1969 - 2005

Brown et al.	2008	Payout ratio, dividends, dummy variables for Banking system	Lintner's partial-adjustment	Dividend forecasts are more accurate than earnings forecasts, especially for firms with stable dividends.	39 Countries	1995 - 2004
Konak et al.	2024	Borsa Istanbul Dividend Index	ANN, GA, Hybrid model	The study uses a GA-ANN hybrid model to predict dividend policies of BIST Dividend Index companies, and validating predictions with real data via an iOS-Android app.	Turkey	2011 - 2021
Vodwal & Negi	2023	Profit, size, Z-score, Tobin's Q, Dividends	Logistic regression, LASSO	Using LASSO and logit regression, large, profitable, liquid, high-market-share Indian firms are more likely to announce dividends.	India	1999 - 2019
Won et al.	2012	Dividend, current stock price, past stock price	GAKR	The GAKR model refines rule-based algorithms with genetic algorithms to forecast dividend policy more accurately and efficiently.	South Korea	1980 - 2000
Bae	2010	Dividends, stock price	SVM	SVM outperforms other models in predicting dividend policy, aiding corporate decisions.	South Korea	1980 - 2000

Diez et al.	2025	Polarity, Previous volume, time passed, number of news items	ML	ChatGPT-extracted news sentiment can predict abnormal intraday returns after dividend announcements, aiding short-term trading.	USA	2023 - 2024
Álvarez-Díez et al.	2024	Firm size, profitability, leverage, dividend yield, growth opportunities	Regression	Machine learning sentiment analysis of dividend announcements predicts short-term abnormal returns, with negative news offering profitable trading opportunities.	USA	2022 - 2023

Empirical Evidence

3.1 Sample Construction and Data

The population of the study consists of annual financial statements from 515 non-financial companies listed on the Stock Exchange of Thailand (SET) over the period from 2000-2024. The data was derived from GuruFocus including the income statement, balance sheet, cash-flow, and key financial ratios for each company and fiscal year. The data was transformed into 223 quantitative features.

In the data cleaning process, financial institutions were removed from the sample due to the balance sheet structure being significantly different from those of non-financial firms which would have been detrimental to the ML models' ability to accurately predict dividend payouts.

After cleaning the data, the final data set contained 6449 firm-year observations with 6080 firm-year observations being used for training and 369 being used for testing which are 95% and 5% respectively. Each observation represents 1 fiscal year for 1 company.

3.2 Dividend Status Classification

Each observation in the sample was assigned to one of four different mutually exclusive classes based on how the Dividends Per Share (DPS) changed over two years following the observed year:

- Grow: The DPS is predicted to increase by more than 5% in the next 2 years.
- Maintain: The DPS is predicted to remain within ±5% in the next 2 years.
- Decline: The DPS is predicted to decrease by more than 5% in the next 2 years.
- Remain Unpaid: The DPS is predicted to remain at 0 in the next 2 years.

The distribution of these statuses among the 369 companies in the sample is detailed below:

Table 2. Distribution of Next 2-year Dividend Status

Dividend Status	**Count**	**Percentage of Sample**
Grow	162	43.9 %
Maintain	29	7.86 %
Decline	107	29%
Remain Unpaid	71	19.24 %
Total	369	100%

Table 2 provides how the 369 companies in the sample were classified based on their dividend performance over a 2-year period. The grow category was the largest, representing 43.9% of the sample while the maintain category was the smallest, representing only 7.86% of the sample.

3.3 Descriptive Statistics

The dataset contains 223 financial variables classified into 8 different categories by following the theoretical framework to provide a comprehensive view of a company's financial statements. This is featured in Table 5 in the appendix.

To identify the details of the dataset, we added descriptive statistics in Table. 3 from the period of 2000-2024. We chose 8 random variables for 8 different categories from 223 variables.

Table 3. Descriptive Statistics

Variables	Max	Min	Mean	Median	Standard Deviation
ROIC % (Return on Invested Capital)	90.90	-279.19	8.32	6.60	11.37
Free Cash Flow per Share	361.49	-379.63	0.60	0.16	9.61
Net Cash per Share	111.28	-3,536.59	-9.47	-2.01	83.38
Dividend Payout Ratio	320.00	0	0.81	0.36	5.40
Debt-to-Equity	3.78	-2.28	0.61	0.38	0.70
Dividend Yield %	117.69	0	3.40	2.50	5.05
Retained Earnings	957,167.13	-103,848.40	6,460.51	561.18	40,125.03
Cash Flow from Operations	322,424.69	-14,107.09	2,399.37	261.22	14,034.03

The ROIC % (Return on Invested Capital) has a mean of 8.32 and a standard deviation of 11.37, ranging from a minimum of -279.19 to a maximum of 90.90. The wide range of the values indicate that there is a vast gap between high performing companies and those that are struggling with capital efficiency.

The Free Cash Flow per Share has a mean of 0.60 and a standard deviation of 9.61, ranging from a minimum of -379.63 to a maximum of 361.49. The wide range of the values indicate that there is a vast gap between companies that have a large inflow of cash compared to those that experience issues with liquidity.

The Net Cash per Share has a mean of -9.47 and a standard deviation of 83.38, ranging from a minimum of -3,536.59 to a maximum of 111.28.

The Dividend Payout Ratio has a mean of 0.81 and a standard deviation of 5.4, ranging from a minimum of 0 to a maximum of 320.

The Debt-to-Equity has a mean of 0.61 and a standard deviation of 0.7, ranging from a minimum of -2.28 to a maximum of 3.78.

The Dividend Yield % has a mean of 3.40 and a standard deviation of 5.05, ranging from a minimum of 0 to a maximum of 117.69.

The Retained Earnings has a mean of 6,460.51 and a standard deviation of 40,125.03, ranging from a minimum of -103,848.40 to a maximum of 957,167.13.

The Cash Flow from Operations has a mean of 2,399.37 and a standard deviation of 14,034.03, ranging from a minimum of -14,107.09 to a maximum of 322,424.69.

3.4 Empirical Patterns by Dividend Status

Table 4. Comparative performance analysis

Algorithm	Iterations	Feature Count	Feature Types (variables)	Remain Unpaid F1 Score	Maintain F1 Score	Grow F1 Score	Decline F1 Score
Random Forest	10	37	Ratio	0.69	0.06	0.64	0.59
Decision Tree	10	37	Ratio	0.55	0.05	0.59	0.49
Boosted Tree	5	37	Ratio	0.67	0.07	0.64	0.57
Boosted Tree	50	16	Per Share	0.70	0.06	0.63	0.62
Boosted Tree	20	53	Ratio + Per share	0.73	0.12	0.67	0.65
Decision Tree	20	53	Ratio + Per share	0.72	N/A	0.65	0.63
Boosted Tree	20	169	Ratio + Items on Financial Statements	0.79	0.07	0.70	0.64
Boosted Tree	20	135	Items on Financial Statements	0.79	0.06	0.65	0.56
Boosted Tree	100	223	Ratio + Per share + Items on	0.77	0.22	0.70	0.70

			Financial Statements				
Boosted Tree	500	223	Ratio + Per share + Items on Financial Statements	0.76	0.22	0.70	0.69
Random Forest	500	223	Ratio + Per share + Items on Financial Statements	0.77	0.21	0.71	0.67
Boosted Tree	500	28	Market Price Related	0.68	N/A	0.65	0.63

The study compares the performance of Boosted Tree, Decision Tree, and Random Forest models across various configurations. The results are reported in Table 4.

The predictive accuracy is measured by F1 scores. Across all models, the remain unpaid category has the highest F1 score reaching up to 0.79 when using the boosted tree algorithm. This suggests that companies that do not pay dividends are more easily forecasted by the ML algorithm. The maintain category presents a challenge for ML models. In several cases, the F1 score is very low or not applicable. Boosted tree models provided the highest F1 scores. Random forest models show competitive results, especially for high amounts of iterations and features. Decision tree models generally underperformed compared to the boosted tree and random forest models. The ML models had significantly higher forecasting accuracy when using all features compared to using categorized features.

In summary, the boosted tree algorithm consistently provided superior predictive power than the random forest and decision tree algorithms.

Conclusion

Predicting dividends is a key challenge in financial economics. Dividends are a critical signal of a company's financial wellbeing, of which is crucial to investors and analysts who are trying to understand a company's future prospects.

Historically, traditional financial models used to forecast dividend policy fail to capture non-linear, complex, and multidimensional relationships. Recent literature has emphasized that ML models have consistently outperformed traditional financial models when it comes to predicting dividend policy. This study attempts to discover which ML method is best for forecasting dividend policy and status. This study also bridges the gap between emerging markets and advanced technological methods such as machine learning.

This study addresses the dividend puzzle by applying ML techniques such as random forest, boosted tree, and decision tree algorithms to predict the dividend status of 515 non-financial companies listed on the SET between 2000 to 2024. The key findings of this paper emphasize that boosted tree algorithms outperform decision tree and random forest models when predicting the dividend status of a company.

Future studies should explore different ML models such as LSTM when investigating which model is best suited for predicting dividend policy. In addition to financial statement data, it may also be beneficial to use alternative indicators such as sentiment analysis from news and media. Finally, future studies should investigate other markets and compare the results of developed and emerging markets using the same techniques.

Appendix

Appendix 1 Data Definition Table

Classification	Variables
Financial Statement Items	Revenue per Share, EBITDA per Share, EBIT per Share, Earnings per Share (Diluted), EPS without NRI, Owner Earnings per Share (TTM), Dividends per Share, Book Value per Share, Tangible Book per Share, Total Debt per Share, Shares Outstanding (Diluted Average), Revenue, Cost of Goods Sold, Gross Profit, Selling, General, & Admin. Expense, Research & Development, Other Operating Expense, Total Operating Expense, Operating Income, Interest Income, Interest Expense, Net Interest Income, Other Income (Expense), Pre-Tax Income, Tax Provision, Tax Rate %, Other Net Income (Loss), Net Income Including Noncontrolling Interests, Net Income (Continuing Operations), Net Income (Discontinued Operations), Other Income (Minority Interest), Net Income, Preferred Dividends, EPS (Basic), EPS (Diluted), EBIT, Depreciation, Depletion and Amortization, EBITDA, Cash And Cash Equivalents, Marketable Securities, Cash, Cash Equivalents, Marketable Securities, Accounts Receivable, Notes Receivable, Loans Receivable, Other Current Receivables, Total Receivables, Inventories, Raw Materials & Components, Inventories, Work In Process, Inventories,

	Inventories Adjustments, Inventories, Finished Goods, Inventories, Other, Total Inventories, Other Current Assets, Total Current Assets, Investments And Advances, Land And Improvements, Buildings And Improvements, Machinery, Furniture, Equipment, Construction In Progress, Other Gross PPE, Gross Property, Plant and Equipment, Accumulated Depreciation, Property, Plant and Equipment, Intangible Assets, Goodwill, Other Long Term Assets, Total Long-Term Assets, Total Assets, Accounts Payable, Total Tax Payable, Other Current Payables, Current Accrued Expense, Accounts Payable & Accrued Expense, Short-Term Debt, Short-Term Capital Lease Obligation, Short-Term Debt & Capital Lease Obligation, Current Deferred Revenue, Current Deferred Taxes Liabilities, Deferred Tax And Revenue, Other Current Liabilities, Total Current Liabilities, Long-Term Debt, Long-Term Capital Lease Obligation, Long-Term Debt & Capital Lease Obligation, Pension And Retirement Benefit, NonCurrent Deferred Liabilities, NonCurrent Deferred Income Tax, Other Long-Term Liabilities, Total Long-Term Liabilities, Total Liabilities, Common Stock, Preferred Stock, Retained Earnings, Accumulated other comprehensive income (loss), Additional Paid-In Capital, Treasury Stock, Other Stockholders Equity, Total Stockholders Equity, Minority Interest, Total Equity, Net Income From Continuing Operations, Change In Receivables, Change In Inventory, Change In Prepaid Assets, Change In Payables And Accrued Expense, Change In Other Working Capital, Change In Working Capital, Deferred Tax, Stock Based Compensation, Asset Impairment Charge, Cash from Discontinued Operating Activities, Cash Flow from Others, Cash Flow from Operations, Purchase Of Property, Plant, Equipment, Sale Of Property, Plant, Equipment, Purchase Of Business, Sale Of Business, Purchase Of Investment, Sale Of Investment, Net Intangibles Purchase And Sale, Cash From Discontinued Investing Activities, Cash From Other Investing Activities, Cash Flow from Investing, Issuance of Stock, Repurchase of Stock, Net Issuance of Preferred Stock, Issuance of Debt, Payments of

	Debt, Net Issuance of Debt, Cash Flow for Dividends, Cash Flow for Lease Financing, Other Financing, Cash Flow from Financing, Beginning Cash Position, Effect of Exchange Rate Changes, Net Change in Cash, Ending Cash Position, Capital Expenditure, Free Cash Flow
Profitability Metrics	ROE %, ROE % Adjusted to Book Value, ROA %, Return-on-Tangible-Asset, ROC (Joel Greenblatt) %, ROCE %, ROIC %, Gross Margin %, Operating Margin %, Net Margin %, EBITDA Margin %, FCF Margin %, Gross-Profit-to-Asset %, Earnings Yield (Joel Greenblatt) %, Forward Rate of Return (Yacktman) %
Cash Flow Metrics	Free Cash Flow per Share, Operating Cash Flow per Share, Cash per Share
Liquidity Metrics	Current Ratio, Quick Ratio, Cash Ratio, Net Cash per Share
Efficiency Metrics	Asset Turnover, Dividend Payout Ratio, Days Sales Outstanding, Days Payable, Days Inventory, Cash Conversion Cycle, Receivables Turnover, Inventory Turnover, COGS-to-Revenue, Inventory-to-Revenue, Capex-to-Revenue, Capex-to-Operating-Income, Capex-to-Operating-Cash-Flow
Capital Structure & Risk Metrics	Debt-to-Equity, Equity-to-Asset, Debt-to-Asset, Liabilities-to-Assets, Degree of Financial Leverage, WACC %, Effective Interest Rate on Debt %, Altman Z-Score, Beneish M-Score, Scaled Net Operating Assets, Sloan Ratio %
Trend Analysis (Growth Metrics)	5-Year RORE %, 1-Year ROIIC %, 5-Year EBITDA Growth Rate, YoY Rev. per Sh. Growth, YoY EPS Growth, YoY EBITDA Growth, Shares Outstanding (Basic Average), Shares Buyback Ratio %, Buyback Yield %
Valuation Metrics	Month End Stock Price, Market Cap, Enterprise Value, Price-to-Owner-Earnings, PB Ratio, Price-to-Tangible-Book, Price-to-Free-Cash-Flow, Price-to-Operating-Cash-Flow, PS Ratio, PEG Ratio, EV-to-Revenue, EV-to-EBITDA, EV-to-EBIT, EV-to-FCF, Shiller PE Ratio,

	Cyclically Adjusted PB Ratio, Cyclically Adjusted PS Ratio, Cyclically Adjusted Price-to-FCF, Dividend Yield %, FCF Yield %, Net Current Asset Value, Net-Net Working Capital, Intrinsic Value: Projected FCF, Median PS Value, Peter Lynch Fair Value, Graham Number, Earnings Power Value (EPV), Highest Stock Price, Lowest Stock Price

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Footnotes

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