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Predicting Dividend Omission Behaviour of Indian Firms using Machine Learning Algorithms

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Abstract

The life-cycle theory of dividends suggests that dividend omissions may indicate significant strategic changes in the firm's life-cycle. Such behaviours at the same time have implications for investor perception as dividend omissions may signal weak operating performance or financial distress situation. A firm's preference for dividend payments relative to omitting dividend paymentsis also used to cater to investor time-varying preferences.This paper aims to test the prediction models of dividend omission behaviour of firms in India.The financial data of 12942 firm-year observations from 2013 to 2018 indicate 55 percent dividend omissions. The paper uses five classes of machine learning algorithmsto predict this behaviour. The multi-layer perceptron (MLP)ANN approach using the RProp algorithm achieves a predictive accuracy of 82.36 percent with an ROC (area under the curve) of 0.901.The feature set relating to the financial parameters of a firm contributes to the prediction accuracy.

JEL Code : C53, D21, G35
Keywords : Dividend Policy, Life Cycle Theory, Machine Learning, Behavioural Finance, Algorithms, Firms, Investors, India

I. Introduction

EARNINGS DISTRIBUTION THROUGH dividends to shareholders has been a well-researched topic in finance. Lintner (1956), in a seminal paper, suggested that managers prefer the stability of dividends and follow a target dividend payout policy. They adjust their payouts towards this target over a period of time. On the theoretical side, Miller and Modigliani's (1961) hypothesis suggests that dividends are pure residual numbers that have no impact on a firm's value. Between these two competing hypotheses, the negative impact of dividend reduction or omission announcements on stock prices is a well-researched topic in finance (Dielman and Openheimer 1984, Healy and Palepu, 1988). Baker and Wurgler (2004) find that stocks deliver higher negative abnormal returns at the time of dividend omission

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announcement. Coupled with the market reaction fact, a survey of CFOs suggest that firms adopt conservative dividend payout policies, primarily in consonance with the Lintner hypothesis (Brav, 2005). Managers strongly believe that markets put a premium on companies with a stable dividend policy. Many empirical studies confirm the stable dividend hypothesis [see Bhat, Pandey and Patel (2019) for a detailed literature review].

Daniel (2007) support the evidence that companies adjust their investment decisions rather than reduce dividends in cash shortfall situations, and DeAngelo (1990) show that even firms facing financial distress situations are reluctant to omit dividend payments. The principal theories that explain the stable dividend hypothesis are risk aversion of investors, lack of investment opportunities, signalling hypothesis, and agency cost explanation. The role of dividends in signalling to deal with information asymmetry between managers and investors has been well documented (Miller and Rock, 1985; Easterbrook, 1984). The role of dividends in disciplining the firm and overcoming problems of free-cash-flow has also been emphasised (Jensen, 1986)

Amid the considerable evidence on the importance of dividends in corporate finance decisions, the dividend omissions must be the last course of action to address financial flexibility or financial distress situations. However, dividends remain an enigma in the field of finance research (Fama and French, 2001). Skinner and Soltes (2009) observe a significant increase in cross-section variation of the distribution of earnings behaviour many US firms omitting the dividend payment. This paper finds a similar cross-section variation in the dividend-omission behaviour of Indian firms. The financial data of 2157 Indian manufacturing and non-financial services firms from 2013 to 2018 indicate that 55 percent of year-firm observations show omitting dividends during 2013 and 2018. The year 2017 shows a spike as 62 percent of firms omit dividend payments. Table I presents the dividend omission behaviour of Indian firms during this period.

Table I
Year-wise Dividend Omissions

Year	Number of Firms	Percent
2013	1128	52%
2014	1162	54%
2015	1160	54%
2016	1164	54%
2017	1335	**62%**
2018	1190	55%
Total Omissions (out of 12942)	7139	55%

Source : Self Computed

This paper focuses on dividend omissions and tests various machine learning approaches to predict this behaviour. The dividend omission behaviour is focused on four reasons.

i First, the life-cycle theory of dividends suggests that dividend omissions may indicate important strategic changes in the firm's life-cycle (Bulan, 2007).

At times, dividend omission may be an optimal policy response for firms when they require significant financial resources to enter into a new growth phase or go through a turnaround effort. Dividend omissions may at times be strategic in nature, providing financial flexibility to the firm. The study of Bulan (2007) suggests that a large number of dividend omissions indicate good news, where omitting dividends indicate a signal of a turnaround after a period of poor performance. In such situations, the firms resume paying dividends within five years of the omission.

ii. Second, the dividend omission changes the category of a firm from dividend-paying to non-dividend paying. This status has significant implications for the specific investor-clientele perception of the firm in some significant manner (Bulan and Subramanian 2008).

iii. Third, Baker and Wurgler's (2004) study suggests that there is a time-varying preference for dividend-paying firms relative to non-dividend-paying firms. According to their proposition, known as catering theory, firms decide to omit paying dividends when investors put a stock premium on nonpayers; managers cater to their demand by not paying dividends. The investor preferences for dividends may also vary over the household life cycle, creating a need for dividend income. The clientele effect may form around age, employment status, opportunities of discretionary incomes, and income groups. The prediction of dividend omission may also contribute to the understanding of the catering theory of dividends.

iv. Fourth, dividend omissions may signal cash sensitivity of investment decisions. The work of Fazzari, Hubbard, and Petersen (1988) shows that that firms with a low dividend-payout ratio were more sensitive to cash flow. Auerbach (2001) suggests that the optimum dividend payment is decided jointly with investment decisions. Auerbach and Hassett (2000) predict that mature firms obtain external equity for investments by retaining earnings and distributing the rest of the funds as dividends, even when dividends payments may have unfavourable tax implications.The dividend payout behaviour helps identifyfirms that might have exhausted their financing options and have decided to rely on internal sources. Also, dividend omissions may indicate poor operating performance or financial distress situations. External finance costs may go high in such cases, and dividend omissions are part of conserving the cash.

To develop and test ML approaches to predict dividend omission, we identify firm-years belonging to manufacturing and non-financial sectors that omitted to pay dividends in any of the years from 2013 to 2018.The feature set relating to financial parameters of size, growth, profitability, efficiency, liquidity, and financial risk is used in developing prediction models.

This study uses select machine-learning algorithms to predict the dividend omissions of Indian companies. Machine learning (ML)uses the partitioning of data procedure first to learn and then test the model for prediction accuracy. In contrast to statistical regression models, ML algorithms exploit and learn complex interactions between predictors and the target variable. The ML approaches do not assume or specify any underlying model ex-ante. It has also been observed that financial data is highly skewed in some cases (for example, total assets as a measure of size), and this may suggest modeling the problem using non-linear systems. The ML algorithms can handle non-linearities in the data and improve prediction compared to linear models.

The financial data of companies is generally large enough to allow the partitioning and execute the learning process. The paper uses five classes of ML algorithms: (a) logistics regression, (b) naive Bayes, (c) decision tree ensembles (decision tree, random forest, gradient boosting trees, (d) support vector machines, and (e) artificial neural networks (probabilistic neural network and multi-layer perceptron).

The study presents preliminary evidence of using the above ML algorithms in dividend behaviour research. It aims to use the results with the same inputs and suggest which ML model performs better in predicting the dividend-omission behaviour. The approaches employed here use automatic classification algorithms and are tenable approaches for predicting the dividend-omission behaviour of companies. These algorithms can handle a large volume of data, including qualitative information. The paper tests these models using both quantitative and qualitative data. Other studies in corporate finance have found these approaches helpful in predicting and developing valid forecasts.These algorithms have already been used in finance and economics literature in private equity exit study, IPO premiums, predicting corporate financial distress, and financial slowdown. These are discussed in section III of the paper.

The approach and application of ML used in this paper also have broader implications for extending this to other fields of corporate finance by taking an alternative approach to predictive aspects of decisions than studying the decisions using causal inference approaches. The study takes the view that dividend omissions are an integral part of financial flexibility and a strategic way to address financial distress situations, prediction of the same, therefore, assumes significant importance(Bulan, Subramanian and Tanlu, 2007). Using a sample of 12942 firm-year observations belonging to manufacturing and non-financial sectors of dividend payouts, of which 55 percent are dividend omissions between 2013 and 2018. The feature set relating to financial parameters of size, growth, profitability, efficiency, liquidity, and financial risk contribute to the prediction accuracy, which is a valuable finding to understand the complexity of the dividend omission behaviour. The variables such as financial risk, growth, and liquidity do not appear to play a significant role in prediction. In contrast, size, profitability, and efficiency play an important role in dividend omission behaviour prediction.

The paper is organized into four sections. Section II describes the variables and data used in the paper and the descriptive statistics of the data. Section III describes the ML models used in the study. A brief review of the finance literature using these approaches is discussed in section III of this paper. Section IV discusses the methodology used in the study. Section V reports the results of the prediction models and a discussion on the predictive performance of the approaches. Following this approach, the paper discusses critical contributions and how this understanding will help us take this forward. The final section discusses the results.

II. Variables and Descriptive Statistics

The data has been obtained from the Prowess corporate database maintained by the Centre for the Monitoring of the Indian Economy India. The study uses a sample of 2157 manufacturing and non-financial service companies. Companies with negative net worth, negative dividends, and net sales less than ₹ 1 million were excluded. The final sample has 12942 firm-year observations. The sample represents 66 percentof the market capitalization of all listed companies in India (₹ 143 trillion as of March 2018 and about 95% of all manufacturing and non-financial service group market capitalization (₹ 94 trillion). The study uses fourteen financial variables belonging to the following six dimensions of a firm.

i. Size
ii. Growth
iii. Efficiency
iv. Profitability
v. Liquidity
vi. Financial Risk

Table II defines the variables used in this study. They are mapped to the above dimensions, and the justification for including these dimensions is discussed below.

Table II

Financial Dimensions, Variables, and Definition

Dimension	Variable	Definition
Dividends	div	dividends paid during the year (including both interim and final dividend)
Size	lnta	natural log of total assets
	lnns	natural log of net sales to represent the size of the firm
Growth	i	investments (both in fixed assets and working capital)
	sg	Growth rate in sales
	gnw	Growth rate in net worth
	gta	Growth in total assets
Efficiency	e	Efficiency measured as net sales to capital employed ratio
Profitability	nm	nm: net margin (PAT/NS)
	roe	roe: return on equity (PAT/NW)
Liquidity	cfons	cash from operations to net sales ratio
	cfota	cash from operations to total asset ratio
Financial Risk	tdce	total debt to capital employed
	stdce	short-term debt to capital employed
	ltdce	long-term debt to capital employed

Source : Self Formulated

2.1. *Size*

Several research studies on dividend-paying behaviour have examined the effect of size on a firm'sdividend payout decisions. For example, Adaoglu (2008) analyzed the effect of size and found that big-sized companies distribute higher dividends than smaller companies. Duygun (2018) and Al-Najjar and Kilincarslan (2016)study also suggest a positive effect of size on the dividend payout. Yýldýz (2014) found that liquidity, size, and profitability variables impact the dividend payout positively. The reasons why size may prefer not to omit dividends is because of agency arguments and issues of signalling. The present study uses a log of net sales and total assets to represent the firm's size.

2.2 *Growth*

The pecking order hypothesisbased on the works of Donaldson (1961) and Myers and Majluf (1984) suggests that managers prefer the internal sources first to meet their requirements, and if the internal sources are not sufficient, they explore external sources. The requirements emanating from new investments and growth requirements make a strong preference for dividend omitting behaviour. Also, Black (1976) suggests that firms that omit to pay dividends may have a portfolio of attractive investment possibilities that might be missed if the firm does not have enough resources. If it makes these investments, the omitting dividend behaviour help companies increase the value of the shares by more than the amount of the lost dividends. According to this hypothesis, if that happens, its shareholders may be better off, and they would end up with higher capital appreciation than what they miss as dividends. The present study uses four growth measures to test dividend omitting behaviour. These measures are investment requirements in fixed assets and working capital requirements, the growth rate in net sales, total assets growth, and net worth growth.

2.3. *Efficiency*

The rate at which the companies turnover their capital employed to indicate the efficiency of operations of the firm. The study uses net sales to capital employed as a ratio to measure efficiency.

2.4. *Profitability*

As per the Lintner (1956) framework, dividend payments are functions of current earnings. Managers adjust paying dividends as per their target payout ratio and adjust towards it over the years. The paper uses net sales margin and return on equity as measures of profitability to predict the dividend omitting behaviour of companies.

2.5. *Liquidity*

The dividend payout requires cash, and therefore liquidity has been found as an important determinant of dividend-paying behaviour. Benito and Young (2003) predict that dividends would be paid only when there is no cheaper way of distributing cash to shareholders. It is rare that firms issue new equity and also pay dividends. Firms with significant cash flows are less likely to omit dividends, as this may better option and a tax-efficient mechanism of returning cash to shareholders. The paper uses cash from operations to net sales and cash from operations to the total asset as ratios to measure the liquidity dimension.

2.6. *Financial risk*

The borrowings can be used to pay dividends, but a higher level of borrowings may result in higher interest commitments and lower dividends in the long run. At times the borrowing covenants will be binding, and the firm's dividend policy is decided by the amount firms have borrowed. Several studies have observed a negative relationship between dividend payout and the use of debt. Firms having high leverage generally experience lower payout of dividends as earnings are first used to service the debt. Firms pay out higher dividends if they have higher profits, liquidity and are large-sized firms. The study uses three measures to measure financial risk: short-term debt to capital employed, log-term debt to capital employed, and total debt to capital employed ratios.

Most of the data used in the paper are quantitative. The study also uses year and sector (manufacturing or non-financial services groups) as qualitative information in the prediction process. The "year" as a variable is critical in predicting behaviour as it captures various macro-economic policies that have implications for dividend omitting behaviour. For example, the number of companies omitting dividends increased significantly after the demonetisation in 2016 (see Table I). The number of year-firm observations which omitted to pay the dividend is 7139 (55%). The sample of dividend-omitting and dividend-paying companies is mostly balanced. The descriptive statistics of variables used in the study are presented in Table III.

Table III
Descriptive Statistics of Key Variables (12942 Firm-Year Observations)

Variables	Median	Mean	Std. Dev.	Skewness
Div (INR millions)	0.000	420.856	3920.309	20.846
lnta	7.325	7.473	2.093	0.267
lnns	7.298	7.218	2.281	-0.191
sg	0.064	0.058	0.460	0.739
gnw	0.069	0.104	0.376	2.623
gta	0.057	0.086	0.260	4.537
e	0.936	1.102	1.923	77.755
nm	0.030	0.007	0.961	-20.451
roe	0.071	0.012	1.888	-44.674
cfons	0.062	0.060	1.128	5.607
cfota	0.058	0.059	0.138	2.393
tdce	0.291	0.311	0.254	0.395
stdce	0.138	0.185	0.188	1.017
ltdce	0.054	0.125	0.163	1.610

Source : Self Computed

III. Machine Learning and its Application in Finance

One of the central topics in the formulation of predictive models is identifying variables that help predict a given outcome. The methods which make an automatic selection, such as stepwise regression (backward or forward), are ideal approaches. But they are often based on strict assumptions regarding the model's functional form or the distribution of residuals or the assumption of linearity. To overcome many of these problems, Sandri and Zuccolotto (2006) suggest machine learning approaches. The finance areas where machine learning has been used include bankruptcy prediction, credit rating prediction, private equity exit prediction, trading, IPO underpricing. This section describes the application of machine learning algorithms in finance research.

The application of machine learning algorithms in financial research is in very early stages. Several financial applications of machine learning include areas such as IPO return prediction,managing risk, and predicting future stock returns, and situations where there are predictable variations in a financial phenomenon. The paper of Tkac and Verner (2016) reviews the applications of artificial neural networks (ANN) in finance research. These applications have been increasingly applied in the area of finance,such as financial distress and bankruptcy problems, predicting stock price, and decision support, with particular attention to classification,approaches. The review suggests that even though ANN methods have often been used, there is huge scope for more research to understand better and improve their functioning. This section provides a brief review of studies that have used ML approaches in finance research.

3.1 *Return Prediction on Financial Assets*

Desai and Bharati (1998) use ANN algorithms and suggest using economic and financial variables to predict the returns on financial assets using ANN. The study finds the ANN forecasts are conditionally efficient with respect to the linear regression forecasts with some confidence.

Thawornwong, Enke and Dagli (2003) find the stock return predictions given by the neural network method are better than those provided by the benchmarks. Maciel and Ballini (2010) study focuses on financial time series forecasting, specifically, the ability of ANN to predict future trends. This paper concludes that ANNs can forecast the stock markets, and tests indicate that ANNs out perform GARCH models in statistical terms. Hanias (2012) study the prediction of the daily stock exchange price index of the Athens Stock Exchange (ASE) using back propagation neural networks. The ANN used in the study indicates an increased possibility of this technique for immediate (daily and weekly) forecasts based on multistep prediction for nine days ahead.

Krauss, Do and Huck (2017) compare three machine learning algorithms of random forests, deep neural networks, and gradient boosted trees on the Standard and Poor's (S&P) 500 stocks. Using the daily returns from 1992 to 2015, the predicted daily one-day-ahead trading signals based on the random forecasts outperform. The findings challenge the semi-strong form of market efficiency.

Loke (2017) analyses the use of quarterly financial ratios in predicting the stock movement of Hong Kong companies from the period 2011-2014. The random forest methods give high accuracy of price movement prediction in the last quarter of 2014 and not in other years. The study speculates the weak prediction in other quarters, may be because of the non-stationary character of the price data. Bootha, Gerding and Megroarty (2014) use an ensemble of random forests approach to describe a model for seasonal stock trading. The RF is found to produce the best out of sample results after exploring the effectiveness of regression techniques and methods for expert weighting.Chou, Ni and Lin (2010) use a genetic algorithm and artificial neuron network to understand factors affecting the stock price using trading data of Baidu stock, which is listed on Nasdaq.

3.2. *IPO Pricing Prediction*

The analysis of IPO returns using machine learning approaches has been the focus of a number of studies. Jain and Nag (1995) develop neural network models to analyze the Initial Public Offerings (IPOs) pricing and predict first-day IPO returns. Reber, Berry and Toms (2005) studied the ability of neural network models to predict the mispricing of initial public offerings (IPOs). The results show that modeling variable interactions and non linearity allows a potentially fruitful approach to studying IPOs. Meng (2008) also uses a neural network approach to predict the first-day closing price of IPOs in the Chinese SME stock market. Using selected financial variables unique to the Chinese SME market and adjusting the scale, a neural network model prediction presents helpful to the investors' decision making. Chen and Wu (2009) use a three-layer neural network model and show that the model fits better with the stock's first day's closing price and dramatically improves the IPO pricing prediction. The study provides a novel approachto forecast the IPO price of small and medium enterprises.

Luque, Quintana, Valls and Isasi (2009) develop an ANN system to predict the initial return of IPOs.The average forecasts provided by various models are bench marked against alternatives, and the results indicate a strong relative performance. Quintana, Luque and Isasi (2005) suggest that a rule-based system defined by a genetic algorithm outperforms in higher predictive performance and robustness to outlier patterns. Compared to linear models, predictions of IPO returns based on machine learning algorithm ssuggest predicting the closing price.Huang (2012) also usethe genetic-based algorithm to select the potentially high-growth IPO stocks. Mitsdorffer and Diederich (2008) and Bastý (2014) use artificial neural networks (ANN) and support vector machine (SVM) to predict IPO initial returns. Wang (2018) use the fuzzy neural network (FNN), an advanced intelligence system of ANN, to predict the under-pricing of US IPOs. Robertson (1998) show that first-day IPO return predictions using neural network models are better than predictions based on the OLS regression. Reber, Berry and Toms (2005) follow the same approach to predict IPO initial returns and confirm neural network models perform better than OLS regression. Quintana (2017) have recently used the random forest to predict the IPO underpricing.

Saìez and Isasi (2017) paper uses IPO data to predict the initial returns. The results indicate that the random forests algorithm outperforms various alternatives based on predictive accuracy. The study establishes the price as the most important variable, and the results support the application of random forests for IPO pricing and IPO trading applications.

Baba and Sevil (2019) study also analyses the IPO initial returns using the random forest to overcome the limitation of linearity assumptionand outliers using a standard linear regression method. The results indicate that the random forest outperforms other methods, and variables such as IPO proceeds and its volume turn out to be the most important predictors of IPO initial returns.

3.3. *Private Equity Exit Prediction*

Bhat and Zaelit (2011) use exit data of 77,160 private equity financed companies to predict the exit type by applying a random forest algorithm. The results suggest that a firm's previous rounds of financing can predict the probability of whether the firm goes bankrupt or whether the firm does the exit of some kind. The results suggest that the random forest approach provides both predictive and explanatory power for various business decisions.

3.4. *Dividend Behaviour Prediction*

Rohov and Solesvik (2016) explore using the size of a firm, the industrial sector in which a firm operates, the concentration of capital, and dividend policy in tree classification random forest algorithm and find a high preference for private placements of shares than going for IPO. The study also found that two-thirds of companies paid dividends when a firm's shares are listed on the foreign stock exchange.

3.5. *Credit Rating or Financial Distress Prediction*

Hajek and Michalak (2013) employ feature selection for corporate credit rating modeling with the improved classification accuracy of the credit ratings. Results suggest that the US rating methodology focuses more on the size of companies and market value ratios, whereas the European methodology relies more on profitability and leverage ratios.

Kalsyte and Verikas (2013) explore using random forest and non-linear data mapping techniques to predict the firm's financial soundness using valuation attributes generally used by the investors.

Yeh, Chi, and Lin (2014) use a hybrid random forest (RF) and rough set theory (RST) approaches to predict intellectual capital (IC) variables. The results indicate that hybrid models produce the best classification rate and the lowest occurrence of Types I and II errors and that IC variables are indeed valuable for going-concern prediction.

3.6. *Equity Risk Premium Prediction*

Routledge (2019) analyzes data used in the asset allocation decision and develops a model using parameters that guide asset allocation and the usual risk aversion parameter. The study uses three distinct and diverse macro economic data sets to implement the model to forecast equity returns (the equity risk premium).Wolff and Neugebauer (2019) study focuses on analyzing equity premium predictions using machine learning predictions.

Compared to linear prediction models, a market timing strategy outperforms a passive buy-and-hold investment.

The present paper uses five classes of ML models. This paper focuses on dividend omissions andattempts to predict this behaviour. To achieve this, we identify firm-years belonging to manufacturing and non-financial sectors that omitted to pay dividends in any of the years from 2013 to 2018. The feature set relating to financial parameters of size, growth, profitability, efficiency, liquidity, and financial risk is used in developing prediction models.

The paper uses five classes of ML algorithms (the details of these approaches can obtained from author on request)

i. Logistics Regression
ii. Naïve-Bayes
iii. Decision tree and Decision Tree Ensembles
– Decision Tree
– Random Forest
– Gradient Boosting Trees
iv. Support Vector Machines
v. Artificial Neural Network
– Probabilistic Neural Network (PNN)
– Multi-Layer Perceptron using RProp Algorithm (MLP)

As can be seen from Table I, dividend omissions sample companies are imbalanced.The random forest approach takes care of this problem using the sample with replacement during training time.

IV. Methodology

The paper uses the KNIME Analytic Platform[1] to perform the learning and prediction analysis of dividend data using ML models. The selected ML models use several classifiers appropriate for the attributes and classes used on the dividend data set.

4.1. *Sample portioning, learning, and out-of-bag testing*

The paper uses the methodology of dividing the complete sample of data in the learning (or training) set and prediction (or test) set. The first partition of the learning data set is used for training the data to fit the model. The second partition of the data set is used to test the model and evaluate the model's prediction performance. This way of data portioning into learning and testing samples is the standard way of testing whether models do not overfit. The learning module of the model evaluation performs well on training data, sometimes with high accuracy perdition, but the model may perform poorly on test data. This way, we are able to test overfitting. If a model performs well at the training level but performs poorly on out-of-sample test data, it may suggest an overfitted model. The paper, therefore, follows the standard approach of learning and testing using a partitioned sample approach to prevent models from overfitting. The study reports the results of the test data only. While doing this, the assumption is that training and test data sets come from the same underlying distribution. The methodology of partitioning the data is essential to gain a realistic view of

Table IV
ML Approaches and Parameters Used in Analysis

	Parameters Available (KNIME)	Parameters Used
Partition	Learn Model Sample: 60% Test sample: 40% Stratified Sampling based on Group variable: Manufacturing & Non-Financial Services Companies	Same across all ML approaches
Logistics Regression	Method Options: · Iteratively Reweighted Least Squares · Stochastic Average Gradient	Iteratively Reweighted Least squares
	Learning rate strategy	Fixed
	Step size	0.1
	Regularization	Prior: Uniform Variance 0.1
Naïve-Bayes	Default Probability	0.0001
	Minimum Standard Deviation	0.0001
	Threshold Standard Deviation	0.0
	Maximum number of unique nominal values	20 per attribute
Artificial Neural Network	Probabilistic Neural Network (PNN)	Number of Epochs 100 Theta Minus 0.2 Theta Plus 0.4
	Multi-Layer Perceptron (MLP) using RProp Algorithm(Normalized Data)	Maximum No. of Iterations 200 Number of Hidden Layers 1 Number of Hidden Neurons Per layer 10
Decision Tree	Quality Measure	Gain Ratio
	Pruning	No
	Minimum No. of Nodes Per Record	2
	Number of Threads	8
	Split (Root Split & Binary Nominal Split)	No
Random Forest	Split Criterion Options: · Information Gain · Information Gain Ratio Gini index	Information Gain Ratio ·
	Tree Depth	10
	Min Node size	1
	Number of models	100
Gradient Boosting Trees	Limit number of levels (tree depth)	4
	Number of models	100
	Learning Rate	0.1
	Attribute Sampling	Sample Square Root
	Attribute Selection	Using Different Set of Attributes for Each Tree Node
	Splits for nominal Columns	Binary Splits
	Splits for Numeric Attributes	Mid-point Splits
SVM	Overlapping penalty	1
	Kernel/parameter: · Polynomial · Hyper Tangent · RBF	Polynomial · Bias 1.0 · Power 1.0 · Gama 1.0

Source : Self Formulated

how the model is likely to behave on a new data set, which the model has not seen before. For this purpose, the paper divides the full sample into two parts. Testing data uses 60 percent of the data selected using a stratified sampling process. Whether the firm belongs to the manufacturing or non-financial services sector, the group affiliation has been used as strata.

One of the essential characteristics of machine learning algorithms is that they depend on how we choose values for various tuning parameters. These values control the adaption of a model to the training or learning set. Table IV describes various parameters of tuning parameters used in ML algorithms used in this study. The parameters to run these models include running each model 100 times through 10 repetitions of 10-fold cross-validation. For example, the tree-depth parameter in the random forest is 10. Similarly, the ANN-MLP procedure has epoch parameter 100 with one hidden layer. During the learning process, the tuning parameters are set to minimize prediction error. For example, the random forest uses the information gain ratio during the training part.

4.2. *Measuring Prediction Quality*

The study evaluates the out-of-sample forecasts after computing predictions for each ML method. The predicted values of the test provide a good idea of how well the models perform. The analysis assesses the relative performance accuracy of each model. The confusion matrix is used to draw the various indicators to test the prediction accuracy of the models. The following Table V is used to develop the definition of these indicators

Table V
Definations of Indicators

	Predicted DO	**Predicted DP**
Actual DO (0)	DO/T (T0)	DO/F (F0)
Actual DP (1)	DP/F (F1)	DP/T (T1)

Source : Self Computed

DO and DP represent the dividend-omitting and dividend-paying firm-year observations, respectively. Based on the confusion matrix where 0 class in DO and 1 is DP companies, and T/F denotes true/false, we define the following four matrices in Table VI.

Table VI
DO & DP Matrix

Measure	**Definition**
Accuracy (% DO and DP Predicted to Total Cases)	(T0+T1)/(T0+F0+T1+F1)
DORecall (Sensitivity) (% DO Predicted of Actual DO)	T0 /(T0+F0)
DP Recall (Specificity) (% DP Predicted of Actual DP)	T1/(T1+F1)
DOPrecision (% DO Predicted of total DO Predicted)	T0/(T0+F1)
DP Precision (% DP Predicted of Total Predicted DP)	T1/(T1+F0)

Source : Self Computed

The above description suggests that each measure is a conditional probability. For example, DO Recall suggests the probability that given a firm is a dividend-omitting firm in our model, and the firm will be dividend-omitting. For each firm, the algorithms provide as output the probability of non-dividend paying behaviour.

We compared methods using the area under the curve (AUC), true and false positive rate cut-offs, and accuracy to judge performance. Specifically, the paper obtains the following measures for each ML approach: sensitivity, specificity, and precision. The study also reports Cohen's kappa to indicate the level of agreement of accuracy statistics. The study builds on the Receiver Operator Curve (ROC) results to obtain the area-under-the-curve (AUC), a commonly-used metric in ML approaches to evaluate the model's predictive performance. The AUC is generated using model predictions to estimate the model's positive and negative predictive value and is an accepted approach to evaluate the model's overall performance. The study does not use the Hosmer-Lemeshow test[2].

V. Results and Discussion

The study uses the data of 2157 manufacturing and non-financial services firms in India for 6 years period from 2013 to 2018. Each firm-year observation is considered as an independent record as each year's unique happenings may influence them. For example, the data suggest a significant increase in dividend omissions in 2017 due to macro-economic policy changes. Consequently, the sample for model computations consists of 12942 observations of dividend payment or dividend omissions. The study uses fourteen financial variables representing six dimensions: firm viz, size, growth, efficiency, profitability, liquidity, and financial risk. Appropriate transformation of strongly skewed variables such as total assets and net sales using logarithmic transformation has been carried out. Table III provides descriptive statistics of variables used in the study. Figure 1 provides a synoptic view of the correlation matrix of all variables.

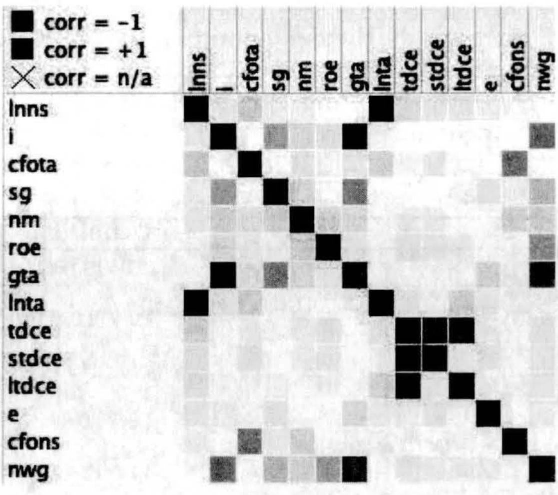


Figure 1
Correlation Matrix of Variables

Table I suggests 55% of sample companies omit paying dividends. The dividend omission category, therefore, is slightly unbalanced. The model's performance needs to be compared with a baseline performance benchmark of 55% and not 50%. It is expected that the ML models should perform reasonably well in terms of various performance measures.

The total sample of 12942 observations is partitioned into training and test samples. The training results are applied to the out-of-bag sample of 5177 observations. Table VII and Table VIII report the overall correctness of classification using the confusion matrix and other predictive statistics of the out-of-bag sample.Using AUC as the primary benchmark to determine model accuracy, the study finds ANN Multi-Layer Perceptron using RProp Algorithm (MLP) performing relatively well in comparison to logistic regression, decision tree ensemble, and SVM. The gradient boosting and random forests are generally considered to perform well with large, unstructured datasets, and these approaches are very close to MLP results.

Table VII

Confusion Matrix and Accuracy Results of ML Approaches Using Test Data

Model	True DO/DP	Predicted DO	Predicted DP
Logistics Regression	True DO	2358	502
	True DP	588	1729
	Accuracy	78.95%	
	Cohen's kappa	0.573 (Moderate Agreement)	
Naïve-Bayes	True DO	757	2103
	True DP	104	2213
	Accuracy	57.37%	
	Cohen's kappa	0.203 (Fair Agreement)	
ANN: PNN	True DO	2767	93
	True DP	1521	796
	Accuracy	68.28%	
	Cohen's kappa	0.33 (Fair Agreement)	
ANN: MLP	True DO	2495	409
	True DP	466	1807
	Accuracy	83.10%	
	Cohen's kappa	0.656(Substantial Agreement)*	
Decision Tree	True DO	2274	568
	True DP	526	1791
	Accuracy	78.52%	
	Cohen's kappa	0.567 (Moderate Agreement)	
Random Forest	True DO	2315	545
	True DP	453	1864
	Accuracy	80.72%	
	Cohen's kappa	0.612(Substantial Agreement)*	
Gradient Boosting Trees	True DO	2371	489
	True DP	470	1847
	Accuracy	82.31%	
	Cohen's kappa	0.642 (Substantial Agreement)*	
Support Vector Machine	True DO	2327	533
	True DP	578	1739
	Accuracy	78.67%	
	Cohen's kappa	0.568 (Moderate Agreement)	

Notes : * Cohen's kappa is a measure of agreement by adjusting the observed proportional agreement to account for the agreement thatis expected by chance.

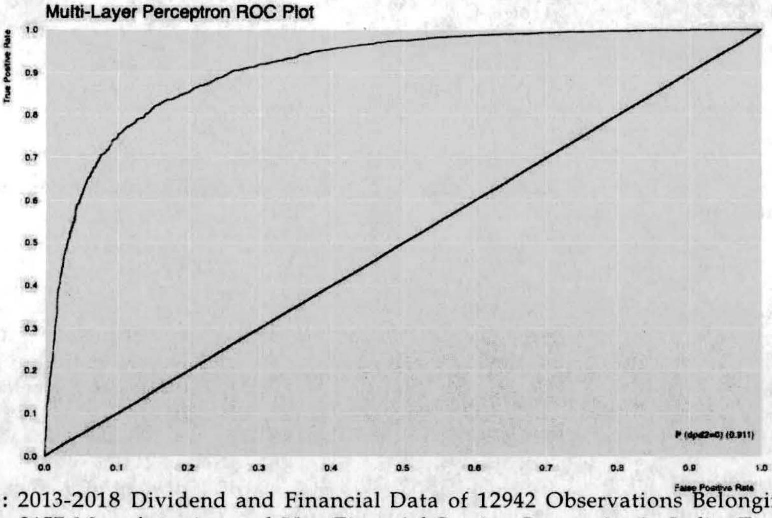
Source : Martin Bland (2015)

Table VIII
Summary Dividend Omission (DO)and Dividend Paying (DP) Results of ML Approaches

	DO Recall (Sensitivity)	DP Recall (Specificity)	DO Pre- -cision	DP Pre- -cision	DO F*	DP F*	Area Under Curve (AUC)
Logistics Regression	0.8245	0.7462	0.8004	0.7750	0.8123	0.7603	0.867
Naïve-Bayes	0.2647	0.9551	0.8792	0.5127	0.4069	0.6673	0.831
ANN: PNN	0.9675	0.3435	0.6453	0.8954	0.7742	0.4966	0.864
ANN: MLP	0.8592	0.7950	0.8426	0.8154	0.8508	0.8051	0.911
Decision Tree Approach	0.8001	0.7730	0.8121	0.7592	0.8061	0.7660	0.817
Random Forest	0.8094	0.8045	0.8363	0.7738	0.8227	0.7888	0.884
Gradient Boosting Trees	0.8290	0.7972	0.8346	0.7907	0.8318	0.7939	0.904
Support Vector Machine	0.8136	0.7505	0.8010	0.7654	0.8073	0.7579	0.869

Note : *F-measure is the harmonic mean of recall and precision
Source : Self Computed

Across all three models, the paper finds theANN-MLP model obtains best performing measures with an overall accuracy of 82.36 percent. This method could predict 82.36 percentin the out-of-bag sample of cases of dividend-omitting behaviour while the misclassifying error is 17.64 percent.The shape of the ROC curve (or AUC) is analyzed to show the effect of different decision thresholds (operating points). The ROC curve is obtained after weighing various possible thresholds within the response range that splits the test sample into the two classes based on the learning model. The area under the curve (AUC), a global performance indicator, measures 0.911 (see Figure 2).



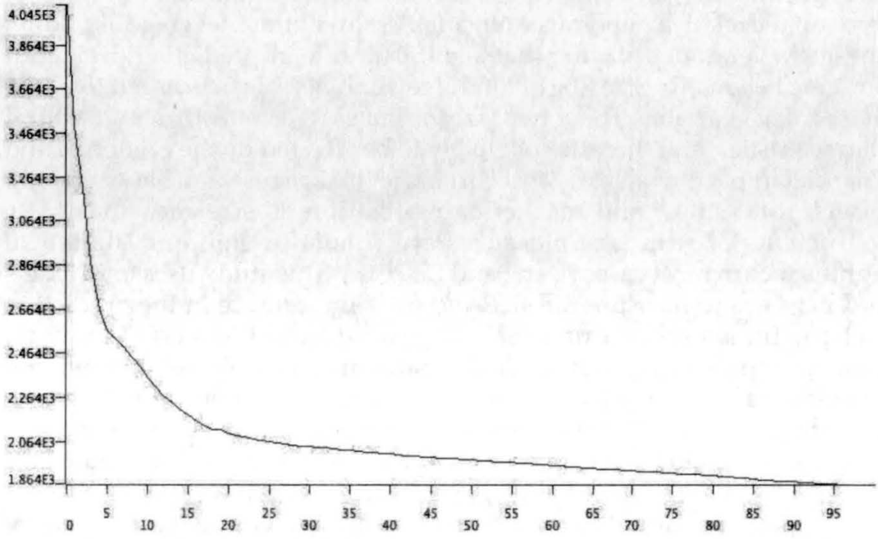
Note : 2013-2018 Dividend and Financial Data of 12942 Observations Belonging to 2157 Manufacturing and Non-Financial Service Companies in India. Train on 60% of data, random stratified sampling using manufacturing and non-financial service groups to stratify. All group analysis.
Source : Self Formulated

Figure 2
Multi-Layer Perceptron ROC Plot: p(dividend omission) = 0.911)

While the methods are reasonably discerning in predicting the dividend-omitting behaviour, some minor changes in selecting variables may further improve the prediction quality. Along with the results, gradient boosting trees and random forest are very close in predicting the dividend omissions. It is suggested these models can be much more helpful in analyzing corporate finance decisions.

Each of the methods used in the study is unique and has its strengths. Logistic regression has been a standard, well-understood,and often used model, particularly in settings where the dependent variable is categorical. ANN-MLP, random forests, and gradient boosting machines have the advantage of considering cross-variable interactions and non-linearities that, if incorporated,would need to be explicitly specified in logistic regression. Working out such a solution is a complex task with datasets, including many potential predictors.

Of the machine learning methods, ANN and random forest are relatively more established and well-known and are easily applied. Meanwhile, gradient boosting machines are growing in popularity, particularly for predictive analytics, and are computable much quicker than random forests in many settings. Figures 2 and Figure 3 report the ROC curve of ANN-MLPand RProp MLP Learner Error Plot, respectively.



Source : Self Formulated

Figure 3
RProp MLP Learner Error Plot

Given the differences between underlying methodologies in the models, we anticipated some divergence across the model results. Accordingly, there were distinct differences in many of the significant predictors in the models. Our results indicate that researchers who attempt to examine predictor-outcome relationships across many variables of interest may consider analyzing their data across several different methods rather than basing their conclusions on a single method. An extension of this work could include an ensemble modeling technique, blending the results of multiple models to create a combined model that considers the various elements of the data that each model has picked out as significant.

The data on dividend payout also indicate that all dividend omissions may not be the same regarding their consistency and declines. In many situations, the dividend omissions may be quickly reversed by resuming to pay dividends, and in some cases, the omissions may persist. Future studies may examine the lags in the resumption of dividend payout once the firm decides to omit to pay dividends. This is important to understand the contours of financial flexibility and how firms cope up with distress situations by adjusting their dividend payouts and the role of profitability. This also helps in understanding the strategic role of dividend omissions.

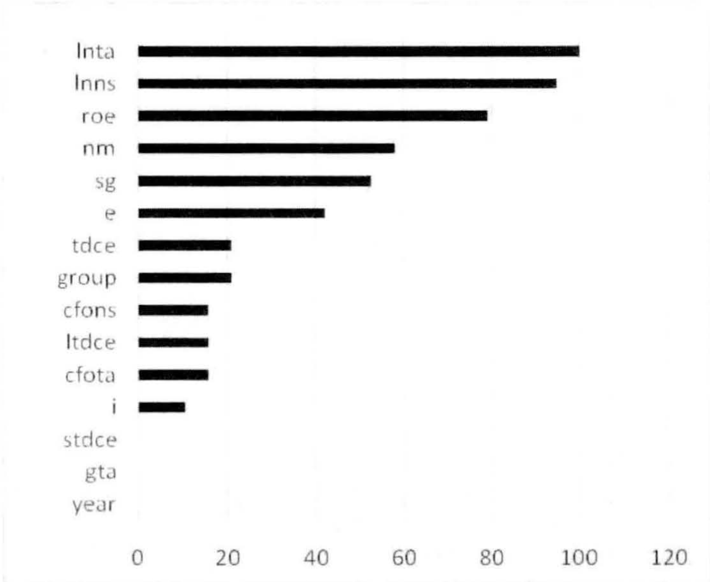
The focus of this study has been on prediction, and the results are somewhat more difficult to interpret from a causal inference perspective.The study uses 14 explanatory variables.

Based on random forest results, which have an accuracy of 80.72% and AUC of 0.884,show the importance of predicting variables (see Figure 4). Size, profitability, and efficiency appear to have a significant influence in terms of the relative importance of variables. In contrast, leverage, liquidity, and growth are not playing that significant role in predicting dividend-omitting behaviour. Size (log of total assets and net sales) turns out to be the most crucial variable. These two size variables reflect the firm's structural characteristics, and these are not likely to be affected by the economic and financial impacts of a year. Most corporate finance research has used total assets, total sales, and market capitalization as size measures. The coefficients of firm size measures are robust in sign and statistical significance in most cases (Dang and Li, 2018). This study uses total assets and net sales to measure the size and their importance in the prediction highest. These two measures represent two different aspects of the firm, total assets providing a view of total firm resources and net sales, providing a measure of product market dominance and competition. Sectoral group affiliation (whether the firm belongs to the manufacturing or non-financial services group) and year does not show high on the importance chart. The importance chart provides also suggests that profitability and efficiency, besides size, are important variables in prediction. However, the variable importance of the random forest approach, which is very close to ANN-MLP prediction accuracy, does not indicate direction. This makes it challenging to infer the relationships based on importance scores alone.

To sum up, the key findings are as follows:

- the MLP-ANN predictive algorithmperforms better based on an AUC measure of 0.911
- MLP-ANN model obtains best-performing measures with an overall accuracy of 82.36 percent

- the classification of out-of-bag observations include 55% of dividend omission firms
- Size, profitability, and efficiency appear to have a significant influence in terms of the relative importance of variables. In contrast, leverage, liquidity, and growth are not playing that significant role in predicting dividend-omitting behaviour.



Source : Self Computed

Figure 4
Importance of Variables (Random Forest)

As stated earlier, this is a very preliminary investigation. Future studies need more in-depth examination and cross-validation of factors that influence dividend omission prediction. In addition to that, the feature or predictor and parameter tuning need to be carried out. The results reported in the present paper performed well and achieved satisfactory accuracy agreement. Parameter tuning was not carried out further. We have not used the models to make a real-time prediction.

The paper lays down a prediction framework, and these models can be used to carry out real-time predictions in the future. It is to be noted that the proposed model predictions provide some segmentation of firms based on their dividend omission behaviour, and it is expected that the results would be sensitive to specific dividend policy decisions of firms and their outlook on investor sentiments. Future studies may look into examining the costs of dividend omission and event triggers of such decisions.The study does not focus on good omissions and bad omissions. Bulan, Subramanian and Tanula (2017) find that good omitting firms have strong fundamentals in better profitability and lower debt at the time of omission. Future studies may focus on predicting the good omitting firms and bad omitting firms. Future studies may also focus on do markets penalise firms for omitting dividends.

VI. Conclusion

The machine learning algorithms have been used in finance research focusing on asset pricing, IPO returns, private equity exit, credit rating, and financial distress predictions. This paper proposes to use supervised ML algorithms to predict the dividend omissions behaviour of Indian firms. It is observed that significantly a large number of companies in India omit paying dividends. As per the data collected and analyzed in this paper, 55 percent of 12942 firm-year observations belonging to manufacturing and non-financial service sectors from 2013 to 2018 omitted to pay dividends. This is true for many other countries. Companies that pay dividends observe smoothening behaviour as predicted by the Lintner framework except when significant macroeconomic changes occur or financial distress situations arise. Why some companies pay dividends and why some companies omit to pay remains an important research question. The predictive power of financial variables to understand this behaviour has been mixed and less reliable. Motivated by recent applications of machine learning (ML) in finance research, this paper measures the performance of five popular classification ML approaches to predict the dividend omission behaviour of Indian companies. These approaches include logistic regression, naive Bayes approach, artificial neural network, decision tree ensembles (random forests, gradient boosted trees), and support vector models. The results provide model prediction results using accuracy and AUC measures and provide a comparison. Given the black-box mechanisms of various models, overall prediction results have been provided and information on feature importance.

The paper reports prediction accuracy, reliability of these predictions, and ROC (area under the curve) analysis across all methods.The analysis presented here attempts to predict dividend omissions using select financial features, influencing a corporate's dividend omission decisions.The results reported establish the high performance of ANN-MLP, gradient boosted trees, and random forests ensemble methods obtaining prediction accuracy performance of 82.36 percent, 82.31, and 80.72 percent, and the AUC values are 0.901, 904, and 0.884, respectively. The results of this analysis are significant as we use multiple ML models for such prediction and report variable importance inference of models emanating from random forest predictions, which have produced significant accuracy agreement.The variables size, profitability, and efficiency play an important role in predicting dividend omission decisions, whereas financial risk, growth, and liquidity have relatively less role in prediction.The findings help advance the use of ML to understand corporate financial behaviour. The analytical approach of this study can be generalized to several different prediction settings in corporate finance. In the corporate finance prediction settings, the modeling approach suggested in the paper could be used to test multiple models, compare performance, and analyze variable importance.

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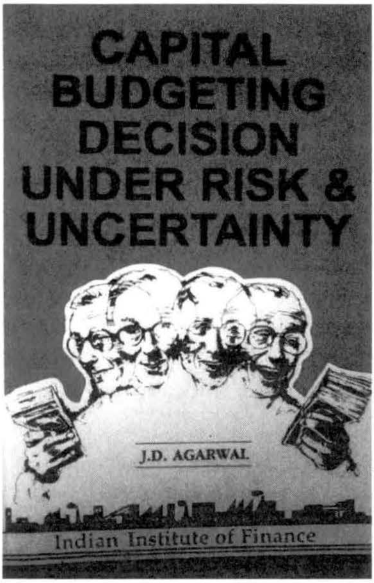

Capital Budgeting Decision under Risk & Uncertainity

Contents

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