PREDICTING DIVIDEND PAYOUT POLICY OF TURKISH FIRMS USING XGBOOST AND MLNN ALGORITHMS

XGBOOST VE MLNN ALGORİTMALARINI KULLANARAK TÜRK FİRMALARININ TEMETTÜ ÖDEME POLİTİKASININ TAHMİN EDİLMESİ

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Abstract

This study aims to predict the dividend payout policy of 211 Turkish firms based on firm-level variables such as cash flow, sales, the age of the firm, earnings per share, etc. Two advanced machine learning algorithms, XGBoost and multi-layer neural networks, are used to classify dividend payout policies. Both algorithms are successful at predicting policy class, but XGBoost gives better results by using additional analysis to find the best hypermeters. Precision and recall values are also analyzed, with each algorithm again providing highly accurate predictions for each of these metrics with approximately 0.8. Using XGBoost's feature importance module, the most determinant factors influencing this prediction are found to be cash flow and size.
Keywords: XGBoost, MLNN, Dividend Policy, Turkey, Machine Learning.

Öz

Bu çalışma 211 Türk firmasının temettü dağıtım politikasını nakit akışı, satışlar, firmanın yaşı, hisse başına kâr gibi firma düzeyindeki değişkenlere dayalı olarak tahmin etmeyi amaçlamaktadır. İki gelişmiş makine öğrenmesi algoritması, XGBoost ve çok katmanlı sinir ağları temettü ödemesi politikalarını sınıflamak için kullanılmıştır. Her iki algoritma da her iki sınıfı da tahmin etmekte başarılıdır ancak XGBoost algoritması en iyi hiper parametreler bulunarak daha iyi sonuçlar üretmiştir. Kesinlik ve duyarlılık değerleri de analiz edilmiş ve yine her iki algoritma da bu iki değere yaklaşık 0.8 olan yüksek değerler sağlamıştır. XGBoost öznitelik modülü ile bu tahminlemede en önemli faktörler nakit ve toplam büyüklük olarak ortaya çıkmıştır.
Anahtar Kelimeler: XGBoost, MLNN, Temettü Politikası, Türkiye, Makine Öğrenmesi.

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1. INTRODUCTION

The dividend payment policy of firms have long been debated in finance theory (Fama & French, 2001; La Porta et al., 2000; Lintner, 1956; Miller & Modigliani, 1961). Academicians have tried to answer questions such as why and how firm pay dividends, whether doing so benefits the firms or not and so on. In addition, in finance theory, the aim of firms is to maximize shareholders' wealth. To maximize shareholders' wealth, firms need to make decisions in many areas, three of which have particular importance for the firm's value in corporate finance: investment (capital budgeting), financing and dividend payout policy. There is a close relationship between a firm's dividend payout decisions and its investment and financing decisions. Hence, dividend payout policy is a crucial factor in finance (Bradley et al., 1998; Damodaran, 2015; Forti et al., 2015; Watson & Head, 2016). The literature on finance examines many financial variables that may affect the dividend payout policies of firms, such as size (Al-Najjar & Kilincarslan, 2016, 2017; Dewasiri et al., 2019; Kanakriyah, 2020; Kuzucu, 2015; Yarram, 2015), cash flow (Dewasiri et al., 2019), return on equity (Ankudinov & Lebedev, 2016; Dewasiri et al., 2019; Farrukh et al., 2017; Kanakriyah, 2020), return on assets (Al-Najjar & Kilincarslan, 2016, 2017; Ferris et al., 2006; Kanakriyah, 2020), sales growth (Amidu & Abor, 2006; Yarram, 2015), the firm's age (Al-Najjar & Kilincarslan, 2016, 2017; Dewasiri et al., 2019; Kuzucu, 2015), earnings per share (Al-Najjar & Kilincarslan, 2017; Farrukh et al., 2017; Kuzucu, 2015), capital expenditures (Yarram, 2015), debt (Yarram, 2015), current ratio, (Kanakriyah, 2020; Kuzucu, 2015) and so on. Hypotheses and models are examined alongside classical regression models, such as pooled OLS, fixed effects, random effects, etc. Unlike in previous studies, we try to predict a firm's dividend payout policy by applying advanced machine learning approaches in the study. Machine learning, which is currently one of the most popular data analysis methods, consists of algorithms that predict outcomes as accurately as possible. The algorithms change based on the type of data being predicted. If the data set contains a set of features that influence the outcome data and if the labeled outcome data is given, supervised learning algorithms are used. Moreover, the supervised learning algorithms are chosen based on the type of outcome data label (regression or classification).

In recent years, machine learning algorithms have been applied to the finance field. For instance, Bae (2010) examines attempts to predict the dividend policy decisions of Korean firms by using support vector machines (SVM), decision trees, and neural networks. The results reveal that SVM performs better than other techniques in forecasting dividend policy. Won, Kim, & Bae, (2012) analyze dividend policy forecasting via genetic algorithm-based knowledge refinement (GAKK) and other models, such as CHAID, CART, QUEST, and C5.0. They find that GAKK is the best suited to forecasting dividend policy. Abdou et al. (2012) investigate the dividend policies of transportation firms by comparing generalized regression neural networks with conventional regressions. According to their findings, neural networks indicate better performance than classical regressions. (Basak et al., 2019; Fiévet & Sornette, 2018) forecast stock prices based on extreme gradient boosting (XGBoost) and produce highly accurate results. Abellán & Castellano (2017); Bequé & Lessmann (2017) and Harris (2015) predict credit scores by applying machine learning models. Huang & Yen

(2019); Kristóf & Virág (2020); Popescu & Dragotă (2018); Wang (2017) and Zheng & Yanhui (2007) examine financial distress and corporate bankruptcy prediction by using different machine learning algorithm models.

In this study, we try to predict the dividend policy of 211 Turkish firms listed on the Borsa Istanbul from 2006 to 2019 by applying two advanced machine learning algorithms XGBoost and multi-layer neural network (MLNN). To the best of the authors' knowledge, this study is the first to predict the dividend policy of Turkish firms. Our model uses 19 financial indicators and a World Uncertainty Index (WUI) specific to the nation of Turkey. The results show that both the XGBoost and MLNN algorithms supply highly accurate predictions of the class of dividend policy adopted by a firm based on the selected factors. Other metrics, such as precision, recall and F1 scores, are also obtained with satisfactorily high accuracy. The remainder of this paper is organized as follows. Section 2 explains the data and research methodology. Section 3 indicates the empirical results, and finally, Section 4 is the conclusion and discussion part.

2. DATA and METHOD

2.1 Data

This study considers firms listed in the Borsa Istanbul (BIST) from 2006 to 2019. Firm-level data variables are obtained from Thomson Reuters DataStream. The World Uncertainty Index (WUI) data of Turkey is taken from its website. Age data of firms is taken manually from Google. The original sample is subjected to several sample selection parameters. Sport teams, utilities, and real estate investment trusts firms are not involved. Firms in the financial sector, such as banks, insurance firms, leasing firms, factoring firms, and other firms related to financial institutions, are not included. Firms with missing data or negative leverage and tangibility in the sample are not included. Firms are included if they have at least four years of consecutive data. After data processing, we have 211 firms that represent 2,408 firm-year observations. Table 1 displays the definition of each variable.

Table 1. *Definition of variables*

Explanatory Variables	Definitions	Source
DIV	If a firm pay dividends in each year, it is coded as "1" and "0" otherwise	Thomson Reuters
CASH	The ratio of cash and cash equivalents to the total assets	As Above
SALES	Annual change in sales growth (%)	As Above
SIZE	Natural logarithm of total assets in current USD	As Above
CAPEX	The ratio of capital expenditure to the total assets	As Above
CF	The ratio of the sum of pretax income plus depreciation to the total assets	As Above
IE	The ratio of interest expense to the total assets	As Above
NCWC	The ratio of non-cash working capital to the total assets	As Above
PPE	The ratio of net fixed assets to the total assets	As Above

STD	The ratio of short-term debt to the total assets	As Above
ROA	The ratio of net income to the total assets	As Above
ROE	The ratio of net income to the total equity	As Above
AR	The ratio of account receivable to the total assets	As Above
AP	The ratio of accounts payable to the total assets	As Above
CR	The ratio of current assets to current liabilities	As Above
EPS	Earnings per share	As Above
ROIC	The ratio of net operating profit after tax to the total assets	As Above
NET MARGIN	The ratio of net income to the net sales	As Above
PRETAX MARGIN	The ratio of profit before tax to the net sales	As Above
AGE	The foundation year of the firm	Google Search
WUI_TURKEY	Annual average of quarterly data of World Uncertainty Index	https://worlduncertaintyindex.com/

2.2. Method

Predicting DIV is a classification problem with binary outcomes Yes/No. These categorical response values are converted into 0/1 type to apply the machine learning algorithms by Python. Extreme gradient boosting and neural networks are two advanced machine learning algorithms that yield high accuracy rates compared to other classification algorithms.

Extreme Gradient Boosting Algorithm (XGBoost), which is a widely used ensemble learning method in machine learning is developed by (Chen & Guestrin, 2016). The algorithm is the optimized version of the Gradient Boosting algorithm and runs ten times faster than the other well-known algorithms (Chen & Guestrin, 2016). The method starts with a base score, and based on this score, the output and actual values are compared to find the residuals. The main objective is to learn the residuals and converge to the actual target (response) values. Since it is a tree-based model, the XGBoost algorithm does not need data normalization, and it is easy to handle the missing data problem. To prevent overfitting, L1 and L2 regularization might also be used. There are also many hyperparameters such as learning rate, maximum depth of the trees, number of estimators and the minimum number of samples to split a node. Moreover, using a cross-validation combination of several hyperparameter values is tried, and the best score giving hyper parameter set is assigned for the model to run.

Another algorithm proposed in this study is Multi-Layer Neural Networks (MLNN) which is indeed a deep learning algorithm, is also widely used for both structured and unstructured data and providing high accuracy results for classification problems. This method proposed by (Rumelhart, Hinton, & Williams, 1986) uses backpropagation to update the node weights to minimize the difference between model outputs and the actual target values. They also define **hidden layers**, which are extra layers other than input and output nodes, which help increase the learning complex features.

MLNN requires data normalization; therefore, in this study, all 19 numerical feature variables are scaled before training this network. Three layers with 128,128 and 64 nodes in each are added to the model. The hidden layers use the "RELU" activation function, while the output node uses the "Sigmoid" function to predict the target values.

For classification problems, the performance measures are Accuracy, Recall, Precision, and F1 – Score. Since the data set is not strongly imbalanced (1403 DIV values are "No" and 1078 are "Yes"), accuracy might be a correct metric because it is simply computed by a total number of correct predictions for DIV divided by the total number of predictions for DIV. Recall, on the other hand, is the ratio of a *number of truly classified DIV=" Yes"* to a number of all DIV=" Yes" values in the data set. In addition to that, Precision is the ratio of number *of truly classified DIV=" Yes"* to a number of all DIV=" Yes" values predicted by the model. F1 Score is another metric that is a combination or the balanced version of recall and precision and is computed by the formula:

$$F_1 = \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

3. EMPIRICAL FINDINGS

The correlation between DIV and the explanatory variables are displayed in Figure 1. According to the correlation coefficients, several features such as SIZE, CF, and AGE are positively and not strongly correlated with DIV and some features like IE, STD and AP are negatively and slightly correlated with the response variable in consideration.

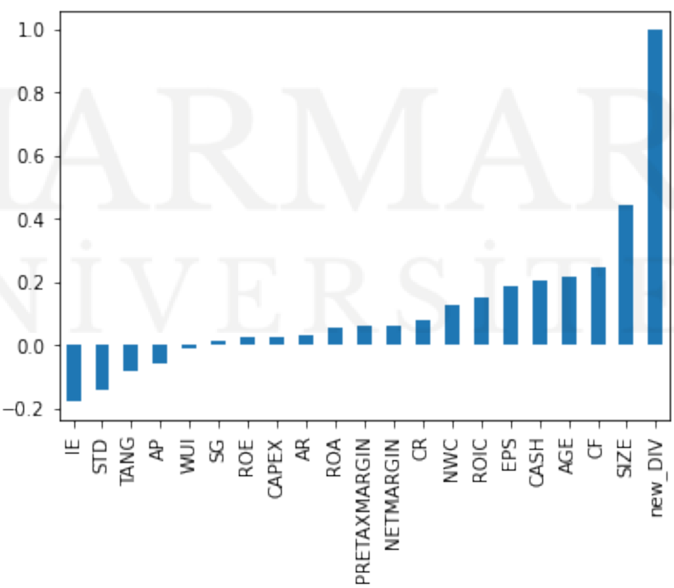

Figure 1. *Correlation between feature variables and the dividend payout policy*

Since the data set consists of high dimensional tabular data, to observe the relationships in between the variables a heat map is drawn in Figure 2. Related to that visualization, there is positive correlation in between NET MARGIN and PRETAX MARGIN, EPS and PRETAX MARGIN, and IE and STD. On the other hand, there is negative correlation in between NWC and STD, IE and SIZE, NWC and IE, and STD and SIZE.

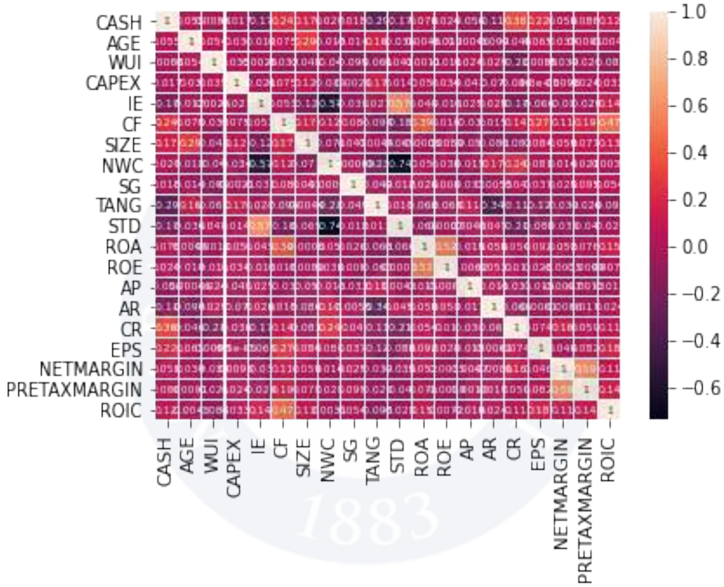

Figure 2. *Heat map for the feature variables and the outcome variable*

In both XGBoost and MLNN algorithms data set is divided into training and test sets with 70% and 30% respectively. DIV column is converted into 0/1 variables. To find the best hyper-parameters randomized search is added to the XGBoost model. The candidate parameters are displayed in Table 2. The best hyper-parameters after fitting the training data with the XGBoost classifier are shown with bold and * in this table.

Table 2. *Hyper parameter settings for the XGBoost algorithm*

n_estimators	**500***	700	1000	
subsample	0.5	0.8	**1.0***	
max_depth	4	5	**6***	7
learning rate	0.1	**0.05***	0.01	
min_samples_split	10	**15***	20	

The confusion matrix for XGBoost algorithm is displayed in Table 3. The matrix shows that 366 positive (DIV=" Yes") out of 744 test data are correctly labeled and 241 negative (DIV=" No" out of 744 test data is correctly labeled. And a total of 137 data are incorrectly classified.

Table 3. *XGboost model confusion matrix*

		Predicted Class	
		Positive	Negative
Actual Class	Positive	366	70
	Negative	67	241

The performance metrics of XGBoost algorithm to correctly predict the class of DIV are summarized in Table 4. Since this is a real-life data, all metrics are satisfactorily high (with an average of 0.82) meaning that the model produces low false negative rate (recall) and the model produces low false positive rate(precision). In addition to that F1 score is 0.78 on the average.

Table 4. *Performance metrics for XGboost algorithm*

State	Binary State	Precision	Recall	F1-score
DIV_TA=No	0	0.83	0.86	0.84
DIV_TA=Yes	1	0.8	0.77	0.79
Weighted Average		0.79	0.79	0.78
Accuracy	0.82			

XGBoost algorithm also shows the important features that have high influence on the model results in Figure 3. The most dominant factor (feature) while predicting the DIV classes is CF and then SIZE. The least important ones are AR and CAPEX.

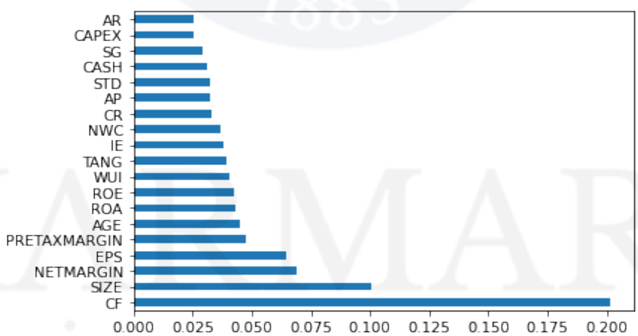

Figure 3. *Feature Importance*

The confusion matrix for MLNN algorithm is displayed in Table 5. The matrix shows that 347 positive (DIV=" Yes") out of 744 test data are correctly labeled and 236 negative (DIV=" No") out of 744 test data are correctly labeled. And a total of 161 data are incorrectly classified.

Table 5. *MLNN model confusion matrix*

		Predicted Class	
		Positive	Negative
Actual Class	Positive	347	89
	Negative	72	236

The performance metrics of MLNN algorithm to correctly predict the class of DIV are summarized in Table 6. Since this is a real-life data, all metrics are satisfactorily high (with an average of 0.78) meaning that the model produces low false negative rate (recall) and the model produces low false positive rate(precision). In addition to that F1 score is 0.78 on the average.

Table 6. *Performance metrics for MLNN algorithm*

State	Binary State	Precision	Recall	F1-score
DIV=No	0	0.83	0.80	0.81
DIV=Yes	1	0.73	0.77	0.75
Weighted Average		0.79	0.79	0.78
Accuracy	0.78			

4. CONCLUSIONS

In this study, we try to predict the dividend payout policy of Turkish firms given 20 selected financial factors such as cash, sales, the age of the firm, earnings per share etc. Two advanced machine learning algorithms, XGBoost and multi-layer neural networks (MLNN), are used to predict a firm's class of dividend payout policy. Both XGBoost and MLNN exhibit high performance (0.8 accuracy on average), but XGBoost with several hyper parameter settings gives the most accurate predictions. XGBoost classifies most of the dividend payout policy types correctly, as does the MLNN algorithm. In classification, the class frequency ratio is approximately 1.4, and no scaling method is used. However, this assumption is open to discussion and the study could be expanded with the data scaling approach. Overfitting does not seem to be a problem in this study, where training error and test error values are similar. However, certain features selected for this study have correlations with each other. These inter-correlated features are assumed to have a weak relationship to each other, and as such, this effect is omitted in this article, but for future studies, the feature selections should perhaps be revised in light of these interdependencies. Moreover, this study spans only 19 years. Performance quality can be better evaluated when there is more data. Finally, this study does not account for the factor of sector classification, which might be another important variable in predicting dividend payout policy classification.

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