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FORECASTING DEFERRED TAXES IN INTERNATIONAL ACCOUNTING WITH MACHINE LEARNING

MAKİNE ÖĞRENMESİ İLE ULUSLARARASI MUHASEBEDE ERTELENMİŞ VERGİLERİN TAHMİNLEMESİ

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Abstract

The aim of this study is to estimate the possible deferred tax values and the TAS-TFRS profit/loss of 31 companies in three different sectors- the wholesale trade, retail trade and hospitality industry- whose shares are traded on Borsa Istanbul (BIST). This estimation is based on the companies' deferred tax values for the years 2015-2019 as well as twelve main economic parameters. Within the context of the study, the deferred tax output parameters, which companies will present in their annual financial reports in 2020, have been estimated using the following methods: the DTA value using the random forest method with an accuracy rate of 0,823, the net DTA value using the artificial neural networks method with an accuracy rate of 0,790, the DTL value using the random forest method with an accuracy rate of 0,823 and the net DTL value using the random forest method with an accuracy rate of 0,887. In addition, it has been discovered that the TAS-TFRS profit/loss, which is one of the output parameters, can be estimated using the random forest method with an accuracy rate of 0,629.

Keywords: International Accounting Standards-International Financial Reporting Standards (IAS-IFRS), Turkish Accounting Standards- Turkish Financial Reporting Standards (TAS-TFRS), Valuation, Deferred Taxes, Machine Learning, Artificial Neural Networks.

Öz

Bu çalışmanın amacı, hisse senetleri Borsa İstanbul (BIST)'da toptan ticaret, perakende ticaret ve konaklama sektörü olmak üzere üç farklı sektörde işlem gören 31 şirketin muhtemel ertelenmiş vergi değerlerini ve TMS-TFRS kar /zararını tahmin etmektir. Bu tahmin, şirketlerin 2015-2019 yılları için ertelenmiş vergi değerlerine ve on iki temel ekonomik parametreye dayanmaktadır. Çalışma kapsamında, şirketlerin 2020 yılında yıllık finansal raporlarında sunacakları ertelenmiş vergi çıktı parametreleri aşağıdaki yöntemler kullanılarak tahmin edilmiştir: 0,823 doğruluk oranı ile random forest yöntemi kullanılarak ertelenmiş vergi varlığı değeri, 0,790 doğruluk oranına sahip yapay sinir ağları yöntemi kullanılarak net ertelenmiş vergi varlığı değeri, 0,823 doğruluk oranı ile random forest yöntemi kullanılarak ertelenmiş vergi yükümlülüğü değeri ve 0,887 doğruluk oranı ile random forest yöntemi kullanılarak net ertelenmiş vergi yükümlülüğü değeri. Ayrıca, çıktı parametrelerinden olan TMS-TFRS kar / zarar değerinin 0,629 doğruluk oranı ile random forest yöntemi kullanılarak tahmin edilebileceği belirlenmiştir.

Anahtar Kelimeler: Uluslararası Muhasebe Standartları-Uluslararası Finansal Raporlama Standartları (IAS-IFRS), Türkiye Muhasebe Standartları- Türkiye Finansal Raporlama Standartları (TMS-TFRS), Değerleme, Ertelenmiş Vergiler, Makine Öğrenmesi, Yapay Sinir Ağları.

GENİŞLETİLMİŞ ÖZET

Çalışmanın Amacı

Bu çalışmada Türkiye'de hisse senetleri Borsa İstanbul (BİST)'da işlem gören toptan ticaret, perakende ticaret ile lokantalar/oteller sektörü olmak üzere 3 farklı sektördeki toplam 31 şirketin 2015-2019 yıllarına ilişkin ertelenmiş vergi değerlerinin yanı sıra on iki farklı temel ekonomik parametre baz alınarak, ilgili sektörlerdeki şirketlerin izleyen yılda raporlayacakları muhtemel ertelenmiş vergi değerlerini ve TMS-TFRS kar/zararını tahminlemek amaçlanmıştır.

Araştırma Soruları

Çalışma kapsamında ele alınan beş araştırma sorusu bulunmaktadır. Bunlar; 1. Çalışma kapsamında incelenen 3 farklı sektördeki şirketlerin yıllık finansal tablolarında raporlayacakları net ertelenmiş vergi varlığı/net ertelenmiş vergi yükümlülüğü değerleri kapsamında, sektörel olarak gelecek yılda elde edilecek toplam vergi avantajı veya vergi yükümlülüğü değerlerinin tahmini olarak hangi düzeyde gerçekleşmesi beklenmektedir? 2. Sektörlerin gelecek yılda elde edecekleri ertelenmiş vergi geliri/ertelenmiş vergi gideri değeri ile toplam TMS-TFRS kar/zarar değerlerinin tahmini olarak hangi düzeyde gerçekleşmesi beklenmektedir? 3. Çalışma kapsamında incelenen sektörlerde net ertelenmiş vergi değerlerinin oluşmasında, hangi ekonomik parametreler ne ölçüde önem taşımaktadırlar? 4. Şirketlerin gelecek yıla ilişkin ertelenmiş vergi değerlerinin tahminlenmesinde, hangi algoritmalar daha başarılı sonuç sağlamaktadır? Şeklindedir.

Literatür Araştırması

Yapılan literatür taramasında yapay sinir ağları yöntemi ile gelecek yıllara ilişkin veri tahminlemesinin yapıldığı yerli ve yabancı kaynaklarda birçok çalışma incelenmiştir. Ancak muhasebe alanında yapay sinir ağları yöntemi ile veri tahminlemesinin yapıldığı çalışmaların sayıca az olduğu gözlenmiştir. Literatürde yapay sinir ağları ile veri tahminlemesinin yapıldığı bu çalışmalardan Etheridge vd. (2007) denetçilerin, müşterinin finansal canlılığının değerlendirmesine yardımcı olacak üç yapay sinir ağı yaklaşımının performansını karşılaştırmak amacıyla oluşturdukları çalışmalarında, olasılıksal sinir ağının sınıflandırmada en güvenilir olduğu, bunu geri yayılım ve kategorik öğrenme ağının izlediği ve kategorik öğrenme ağının ise en az maliyetli olduğu sonuçlarına ulaşmışlardır (Etheridge, Sriram, Hsu, 2007). Yapay sinir ağları modelinin kullanıldığı başka bir çalışmada Altunöz (2013) banka başarısızlıklarını yapay sinir ağları modeli ile önceden tespiti etmeye ilişkin oluşturduğu çalışmasında, modelin başarısızlıktan bir yıl veya iki yıl öncesi için yüksek öngörülü sonuçlar sağladığı sonucuna ulaşmıştır (Altunöz, 2013). Katar Borsası (QE) endeksi verilerini kullanarak bir sonraki işlem gününe ilişkin kapanış fiyatını tahmin etmeye çalıştıkları çalışmalarında

Fadlalla vd. (2014) geçmiş 3 yılın verilerini esas alarak, yapay sinir ağlarının (QE) Endeksini yüksek oranda doğru tahmin etmek için etkili bir modelleme tekniği olduğu sonucuna ulaşmışlardır (Fadlalla and Amani, 2014). Çalışmalarında G-7 ülkelerinde enflasyon tahmini için farklı yapay sinir ağı modellerini değerlendirerek, uygun bir model oluşturmayı amaçlayan Gupta vd. (2015) ise, Tüketici Fiyat Endeksi'ne dayalı enflasyon tahminleri ile enflasyon oranının yakın gelecekte marjinal olarak düşmesinin beklendiği sonucuna ulaşmışlardır (Gupta and Kashyap, 2015). Persio ve Honchar (2016) borsa endekslerini yapay sinir ağı yaklaşımını kullanarak algoritmalarını S & P500 ve FOREX EUR / USD tarihsel zaman serilerinde test etmeye ve FOREX çerçevesinde S & P500 veya dakikalar söz konusu olduğunda son n güne ait veriler temelinde eğilimi tahmin etmeye çalışmışlardır. Çalışmanın sonucunda ise temel sinir ağları yaklaşımlarından daha iyi performans gösteren dalgacık ve CNN kombinasyonuna dayanan yeni bir yaklaşım sunmuşlardır (Persio ve Honchar ,2016). Yapay bir sinir ağı yöntemi ile Malezya'daki küçük piyasa kapitalizasyon şirketlerindeki hileli finansal raporlamayı tahmin etmedeki etkinliğini araştırdıkları çalışmalarında Omar vd. (2017), bu yöntemin hileli finansal raporlamayı tahmin etmek için kullanılan diğer istatistiksel tekniklerden daha başarılı olduğu sonucuna ulaşmışlardır (Omar, Johari, Smith, 2017). León vd. (2017) yapay sinir ağları yöntemi ile, Kolombiya bankalarının bilanço verilerini inceleyerek bunları bir yapay sinir ağı örüntü tanıma yöntemi ile sınıflandırmanın mümkün olup olmadığını test ettikleri çalışmalarında, yapay sinir ağının bir bankayı bilançosu ile tanıyabildiğini ispatlamışlarıdır (León, Moreno, Cely, 2017). Sun vd. (2018) kredi kartı temerrüt riskinin modellemesinde yapay sinir ağı yöntemini kullandıkları ve kredi riski alanında ortaya çıkan yapay zeka teknolojisi olarak derin öğrenme potansiyelini araştırdıkları çalışmalarında, yapay zekanın finansal kurumlar ve kredi büroları açısından, kredi riskinin değerlendirmesini destekleyici katkı sağladığı sonucuna ulaşmışlardır (Sun ve Vasarhelyi, 2018). Kurumsal iflasın tahmin edilmesine ilişkin bir sinir ağının oluşturulmasını ele aldıkları çalışmalarında Hosaka (2019), şirketlerin finansal tablolarından elde ettikleri bazı finansal oranları gri tonlamalı bir görüntü olarak temsil etmiş ve bu işlem kapsamında oluşturulan görüntüyü evrişimli sinir ağını eğitmek ve test etmek amacıyla kullanmışlardır (Hosaka, 2019). Yapay sinir ağlarının kullanıldığı başka bir çalışmada Singh vd. (2019) sahtekarlık tespitinin denetimi kapsamında geliştirdikleri öngörülü bir model ile gerçek muhasebe verilerinde, anormal işlemlerin tespitini mümkün kılarak denetimde manuel müdahale ve işlem süresinde önemli bir azalma sağlamışlardır (Singh, Lai, Vejvar, Cheng, 2019). Abraham (2019) ise çalışmasında yapay sinir ağları kapsamında kripto bir para biriminin fiyat hareketlerinin, makine öğrenme algoritması ve Johansen Testi kullanılarak entegre edilip edilemeyeceğini ele aldığı çalışmanın sonucunda sinir ağlarını içeren makine öğrenme algoritması ile kripto para birimi fiyatlarının tahmin edilmesine uygun olduğunu ortaya koymuştur (Abraham, 2019). Ding vd. (2020) sigorta şirketlerinin zarar rezervlerine ilişkin tahminleri kullanarak, makine öğrenimi ile üretilen zarar tahminlerini, inceledikleri çalışmasında, beş sigorta şirketinden dördünde finansal tablolarda rapor edilen fiili yönetim tahminlerinden daha başarılı olduğu sonucuna ulaşmıştır. Elde ettiği bulgular makine öğrenme tekniklerinin muhasebe tahminlerini iyileştirmede yöneticiler ve denetçiler için yararlı olabileceğinin yanı sıra finansal bilgilerin yatırımcıların yararlılığını da arttırabileceğini savunmaktadır (Ding, Lev, Peng, Sun, Vasarhelyi, 2020). Bu kapsamda güncel başka bir çalışmada Maiti vd. (2020) tarafından oluşturulmuş ve yedi kripto para birimini doğrusal olmayan tahmin modelleri kullanarak tahminlemeye çalıştıkları çalışmadır. Yazarlar bu çalışma ile sinir ağları gibi doğrusal olmayan modellerin kullanımı ile kripto para birimlerinin kaotik ko -hareketlerini tahminlemişlerdir (Maiti, Vyklyuk, Vukovic, 2020).

Yöntem

Literatürde yapay sinir ağları yöntemi ile gelecek yıllara ilişkin verilerin tahminlenmeye çalışıldığı çalışmalar daha çok regresyon ile gelecek yıllardaki değerlerin tahminlenmesine dayanmaktadır. Ancak bu çalışmalar yüksek hata değerlerine sahiptir veya çok fazla veriye ihtiyaç duymaktadır. Bu çalışmada ise değer tahmini yerine değer kategorisinin classification ile tahmini yapılarak firmanın gelecekteki ertelenmiş vergi durumlarının modellenebilir bir hale getirilmesi için bir metot önerilmektir. Önerilen bu yöntem ile çalışma kapsamında incelenen sektörlerdeki şirketlerin net ertelenmiş vergi değerlerinin oluşmasında, hangi ekonomik parametrelerin ne ölçüde önem taşıdıkları ve gelecek yıla ilişkin ertelenmiş vergi değerlerlerinin tahminlenmesinde, hangi algoritmaların daha başarılı sonuç sağladıkları belirlenebilmiştir. Çalışma kapsamında gelecek yıla ilişkin ertelenmiş vergi değerlerinin tahminlenmesinde Orange 3 programı kullanılmıştır.

Sonuç ve Değerlendirme

Çalışmanın sonucunda şirketlerin 2020 yılında yıllık finansal raporlarında sunacakları ertelenmiş vergi çıktı parametreleri aşağıdaki yöntemler kullanılarak tahmin edilmiştir: ertelenmiş vergi varlığı değeri 0,823 doğruluk oranı ile random forest yöntemi kullanılarak, net ertelenmiş vergi varlığı değeri 0,790 doğruluk oranına sahip yapay sinir ağları yöntemi kullanılarak, ertelenmiş vergi yükümlülüğü değeri 0,823 doğruluk oranı ile random forest yöntemi kullanılarak, net ertelenmiş vergi yükümlülüğü değeri 0,887 doğruluk oranı ile random forest yöntemi kullanılarak tahminlenmiştir. Ayrıca, çıktı parametrelerinden TMS-TFRS kar/zarar değerinin de 0,629 doğruluk oranı ile random forest yöntemi kullanılarak tahmin edilebileceği belirlenmiştir. Ayrıca çalışmada gelecek yıllara ilişkin ertelenmiş vergi değerlerinin makine öğrenmesinde sınıflandırma yöntemi kullanılarak yüksek bir başarı oranıyla tahmin edildiği sonucuna ulaşılmıştır.

1. INTRODUCTION

The TAS 12 Income Taxes Standard also covers taxes paid through withholding in profit sharing to the company in the position of a reporter due to its subsidiaries, affiliates and joint agreements, as well as the taxes calculated on the corporate income. In addition, the scope of this standard also includes principles regarding the presentation of income taxes in the financial statements and the recognition of the deferred tax assets or unused tax benefits resulting from the unused losses of the previous years (Public Oversight Accounting and Auditing Standards Authority, TMS 12).

The differences between the book value of the enterprises' assets or liabilities, which affect the profit when recovered or paid, and the values of these assets or liabilities in terms of tax related matters may cause temporary differences within TAS 12 Income Taxes (Çelik, 2014; Public Oversight Accounting and Auditing Standards Authority, TMS 12). Even though the temporary differences are deemed important in the formation of deferred taxes; continuous differences are definitely not taken into account (Karakaya and Sevim, 2016). Temporary differences may arise from the difference between the time of occurrence of income or expense items and the time of recognition of these items by the tax legislation, as well as the difference between the valuation measures of the tax legislation and those of accounting principles. These temporary differences between the accounting results and the measurable income may be reversed in the following periods. Thus, those differences may disappear in the future and lead the accounting profit and financial profit to be reported with different figures (Koç, 2018; Özkan, 2009). Temporary differences resulting from timing may affect a company's future performance. However, companies that recognize the temporary differences earlier will perform considerably better in the future than companies that recognize them later. For companies that don't pay taxes, accounting can be associated with future performance instead of timing. However, when companies that are able to pay their taxes decide to account their deferred taxes, the great increase in the amount of current debt may result in the postponement of the action (Gaeremynck and Van De Gucht, 2004). On that note, if the deferred taxes resulting from timing and valuation differences result in a reduction in future taxable income, they can be deducted from the tax base when calculating. But if they result in increasing the future tax payments, they can be added to the tax base (Public Oversight Accounting and Auditing Standards Authority, TMS 12; Oxner, Oxner, and Phillips, 2018). In this context, the values of the deferred tax assets (deductible temporary differences) or deferred tax liabilities (taxable temporary differences) are calculated by multiplying temporary differences by 22% (İnstitutions Tax Law, 2006) which is the corporation tax rate declared for 2020 in Turkey.

It is aimed in this study to make an estimation of the companies' deferred tax values in 2020, which will be presented in their annual financial reports, with a classification model created with machine learning. For this purpose, the deferred tax assets/liabilities, the net deferred tax assets/liabilities, the deferred tax income/expense and TAS-TFRS profit/ loss values of the companies have been estimated. The estimation of these values was based on the data of the 2015-2019 period for

31 companies operating in wholesale trade, retail trade and restaurants/hotels sectors, whose shares are traded on Istanbul Stock Exchange (BIST) and also twelve main economic parameters in Turkish economy.

There are other similar studies in the literature in which the data of the following years were attempted to be estimated using the artificial neural networks method. Abraham (Abraham, 2019), has discussed whether the price movements of a cryptocurrency within the scope of artificial neural networks can be integrated using the machine learning algorithm and the Johansen Test. As a result of the study, it was revealed that cryptocurrency prices are suitable to be estimated by the machine learning algorithm including neural networks (Abraham 2019). In their study, in which they estimate the losses of insurance companies with machine learning (Ding et al., 2020) reached the conclusion that in four of the five insurance companies, the estimation by machine learning was more successful than the actual management estimates reported in the financial statements. As part of their findings, they argued that machine learning techniques can be useful for the managers and auditors in improving accounting estimations and that financial information can also increase the effectiveness of investors (Ding et al., 2020). In that regard, another contemporary study was carried out by Maiti et al. (2020) in which they estimated seven cryptocurrencies by using nonlinear estimation models. The authors predicted the chaotic co-movements of the cryptocurrencies with this study by using nonlinear models such as neural networks. A summary about other studies in accounting on data estimation with artificial neural networks is presented in Table 1.

Table 1. Other Studies in Accounting on Data Estimation Using Artificial Neural Networks

Machine Learning Method	Aim	Performance Metric	Citation
Classification process was made. ANN model, a totally connected backpropagation model with three neuron layers	Linear discrimination analysis (LDA) on estimating corporate credit ratings based on the financial table data, to provide a comparative analysis of estimation performances against a linear estimation model.	Accuracy ANN 0.79 LDA 0.33	(Kumar and Bhattacharya 2006)
Classification process was made. Simple static logit model and Genetic algorithm (GA) model	Examining the relative performance of models in predicting the bankruptcies of companies and determining which conditions the models perform better under.	Accuracy 0.931(1y) 0.948(2y) 0.977(3y)	(Bateni and Asghari 2020)
Statistica software was used for processing the data. Regression and several distribution functions were used through linear regression and neural structures.	Estimating The Price Of Palladium In New York Stock Exchange.	Accuracy r^2 correlation value: 0.998	(Vochozka 2018)
Classification process was made. Artificial neural network, bayesian network, discriminant analysis, logistic regression analysis and support vector	Detecting Fraud In Financial Reporting.	Accuracy BN: 0.658, DA: 0.62, LR: 0.679, ANN: 0.75, SVM: 0.67	(Mohammadi et al. 2020)

In this context, the studies carried out with machine learning are mostly based on the estimation of the future values by regression. But those studies either have high error values or need much more data. In this study, a method that estimates value category by classification instead of value estimation is proposed in order to estimate the deferred tax value ranges that companies will report in the future. It is noteworthy to mention the contributions of this proposed method to the study;

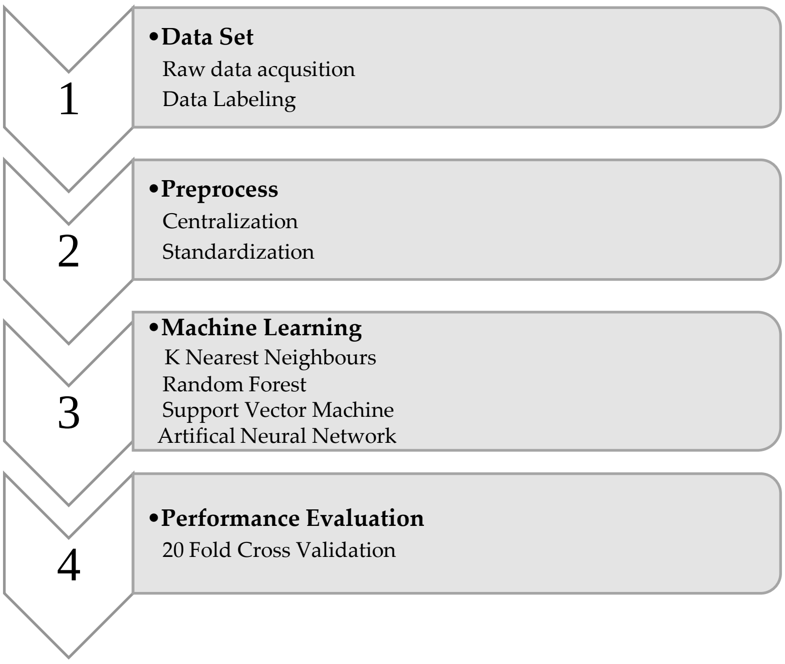
- The deferred tax asset/liability values, which will be reported next year in the annual financial statements of the companies in 3 different sectors examined in the scope of the study, will be estimated.
- The deferred tax income/expense value and TAS-TFRS profit/loss annual values, which the companies will report next year, will be estimated.
- The effect of the deferred tax income/expense value -which will be reported by the companies in the wholesale trade, retail trade and restaurants/hotels sectors next year- on the total tax income/expense that the government will collect will be determined in the study.

It will become possible to determine which algorithms are successful and how successful they are in the estimation of the next year's deferred tax values.

2. MATERIAL AND METHOD

The aim of this study is to estimate the deferred tax values and TAS-TFRS profit/ loss that the companies- whose shares in Turkey are traded on BIST at wholesale trade, retail trade and restaurants/hotels sectors- will present on their annual financial reports of 2020. The method consist four main steps. The first step is data acquisition and preparation of data set. The second step is preprocessing which includes centralization and standardization. The third is machine learning step. In this step K nearest neighbours, random forest, support vector meachine and Artifical neural network methods is used. The last step is performance evaluation and selection best learning method. The method suggested for this pupose is summarized in Figure 1.

Figure 1. Proposed method flowchart



2.1. Dataset and Properties

The data set, consists of the deferred tax values presented in the 2015-2019 period annual financial reports of the companies whose shares are listed in the wholesale trade, retail trade and restaurants/hotels sectors in BIST as well as the values for other accounts and annual average main economic indicators for the same period. The 31 companies from different sectors that compose the data set, the acronym of company names and sectors are presented in Table 2. Estimations for the following year will be made based on the deferred tax values that these companies presented on their annual financial reports for the 2015-2019 period and twelve main economic parameters.

The data to be used as output and input parameters for the estimation are presented respectively in Table 2 and Table 3. The input parameters in Table 3 are of three different types: numeric, 3 category and 5 categories. Numeric parameters can be assigned values in a wide numerical range. Categorical data are divided into 3 or 5 categories depending on their types. If the definition range is equal to zero for the 3-category value, the label 0 will be used; if it is greater than zero and less than 10×109, the label 1 will be used and if it is greater than 10×109, the label 2 will be used. For 5 categories, if the value is between -50×103 and 50×103, the label 0 is used. If it is between 50×103 and 10×109, the label 1 is used. If it is greater than 10×109, the label 2 is used. If it is between -50×103 and -10×109, the -1 value is used and if the value is less than -10×109, the label -2 is used.

However, the categorical distributions of net DTL, TAS-TFRS profit/ loss and DTIECO (Deferred tax income/expense effect due to continuous operations) data showed an unbalanced distribution because of the labeling above. Therefore, in labeling for this data, the net DTL is labelled 0 for values equal to/greater than 0, 1 for values between -1 and -10×105 and 2 for values less than -

10×105. For TAS-TFRS profit/ loss data; the label 0 is used for values between 0 and 50×105, the label 1 is used for values between 50×105 and 10×109 and the label 2 for values less than 0. For DTIECO data; the label 0 is used for values between 0 and 50×104, the label 1 for values greater than 50×104 and the label 2 for values less than 0.

The annual financial reports of the companies analyzed in this article can be accessed on the website of Public Disclosure Platform (KAP), *www.kap.gov.tr* and the main economic parameters announced by the Ministry of Treasury and Finance on their official website can be accessed at *www.hmb.gov.tr/ekonomik-gostergeler*. The economic parameters, which are presented in this study, were based on the annual average values of the 2015-2019 period, published on the official website of the Treasury and the Ministry of Finance. However, since the value of the quarterly (January-February-March) growth rate in 2019 compared to the previous year was only declared in the “gross domestic product” parameter as 0.09 (Ministry of Treasury and Finance, Economic İndicators), this value was multiplied by four and included in the analysis as the annual value.

Table 2. The Deferred Tax Evaluated as An Output Parameter within The Scope of The Study and Profit/Loss Parameters according to TAS-TFRS

Abbreviation	Long Version
DTA_T	Deferred tax assets of the next year
Net DTA_T	Net deferred tax assets of the next year
DTL_T	Deferred taxes of the next year
Net DTL_T	Net deferred taxes of the next year
DTIECO_T	Continuing operations deferred tax income/expense effect of the next year
TAS-TFRS K/Z_T	Next year's profit/loss based on Turkish accounting standards-Turkish financial reporting standards
Abbreviation	Long Version

Table 3. The Parameters Regarding Accounts other than Deferred Taxes Evaluated As Input Parameters and Basic Economic Indicators in The Study

Abbreviation	Definition	Parameter
PTİ(E)	Period tax income/(expense): It refers to the tax income and expenses of the companies applying TAS/TFRS that they calculated based on the legislation and the financial profits of continuing operations on their comprehensive profit/loss statements (Koç, 2018).	3 Category
TTİ(E)	Total tax income/(expense) from continuing and discontinued operations: It refers to the sum of deferred tax income/(expenses) in the comprehensive profit/loss table arising from continuing operations and the tax income/expenses of the period calculated over taxable profit in line with the related legislation (Koç, 2018).	3 Category
F P/L	Financial profit/loss: It refers to the total profit/loss value found by adding the unacceptable expenses in terms of tax law to the commercial profit and subtracting the non-taxable income (Kohavi, 1995).	5 Category
TCMB-OBR	The Central Bank of the Republic of Turkey - Overnight Borrowing Rate (annual average): It is the annual average interest rate that a bank whose interest burden is experiencing a temporary liquidity shortage accepts to pay in order to take short-term loans from the Central Bank (Kumar and Bhattacharya, 2006)	Numeric
MB-BVFO	TCMB Overnight Lending Rate (annual average):): It is the average annual interest rate that a bank whose interest yield is experiencing a temporary	Numeric

	liquidity excess accepts to receive when depositing this fund to the Central Bank so that it utilizes the excess fund and obtains an interest yield (Kumar and Bhattacharya, 2006)	
GRGDPCY	Growth Rate of Gross Domestic Product Compared to the Previous Year: It refers to the economic growth compared to the previous year (İnstitutions Tax Law, 2006).	Numeric
YEA$R	Year-End Average Dollar Rate (TL): It refers to the average Turkish Lira (TL) equivalent of the purchase-sales prices of dollar at the end of the year (Küçük 2014)	Numeric
YEA€R	Year-End Average Euro Rate (TL): It refers to the average Turkish Lira (TL) equivalent of the purchase-sales prices of Euro at the end of the year (Küçük 2014).	Numeric
YEGA	Year-End Gold (world average $/dust): It refers to the value of gold considered a metal. In this study, the world average of the $/dust value of gold is taken as the basis (León et al., 2017).	Numeric
UR	Unemployment Rate: It refers to the relative weight of the unemployed population in the total workforce (Maiti et al., 2020).	Numeric
CPIAPC	Consumer Price Index Annual Percentage Change: It refers to the annual percentage change in the prices of the basket of goods and services purchased by consumers (León, Moreno, and Cely 2017).	Numeric
DPPIAPC	Domestic Producer Price Index Annual Percentage Change: It refers to the annual percentage change in the prices of the basket of raw materials, intermediate goods and manufactured goods (León et al., 2017).	Numeric
BIST-TV	Istanbul Stock Exchange (BIST)Traded Value: The indicator that affects the market in BIST and expresses the total monetary value of all transactions (Masand, Linoff, and Waltz, 1992).	Numeric
IMP	Imports (million): It refers to the sales to foreign countries in exchange for foreign currency. Within the scope of the study, the import parameter is expressed in millions (Mohammadi et al., 2020).	Numeric
EXP	Exports (million): It refers to the purchase of goods manufactured abroad by the domestic buyers. Within the scope of the study, the export parameter is expressed in millions (Omar, Johari, and Smith, 2017).	Numeric
DTA	Deferred tax asset: It refers to the future transferrable amount of deductible temporary differences, which can be deducted from the tax base in the future because even though the accounting principles register them as expenses in the current period, the Tax Legislation considers them to be expenses in the future periods (Oxner et al., 2018).	3 Category
Net DTA	Net deferred tax asset: When we subtract the deferred tax liability amount from the deferred tax asset amount, the remaining amount refers to the deferred tax asset amount (Özkan, 2009).	3 Category
DTL	Deferred tax liability: It refers to the future transferrable amount of taxable temporary differences, which are added to the tax base in the future because even though the accounting principles register them as income in the current period, the Tax Legislation considers them to be income in the future periods (Oxner et al., 2018).	3 Category
Net DTL	Net deferred tax liability: When we subtract the deferred tax liability amount from the deferred tax asset amount, the remaining amount refers to the deferred tax liability amount (Özkan, 2009).	3 Category
DTI/ECO	Deferred tax income/expense effect due to continuous operations: For companies applying TAS-TFRS, the concept refers to the deferred tax effects which are added in the other comprehensive income section in the comprehensive profit/loss table and which arise from the transactions/events resulting from the continuing operations at the current period (Koç, 2018).	3 Category
TAS-TFRS P/L	Profit/loss based on Turkish accounting standards-Turkish financial reporting standards: It refers to the profit/loss of the period before tax expense (Kohavi, 1995).	3 Category

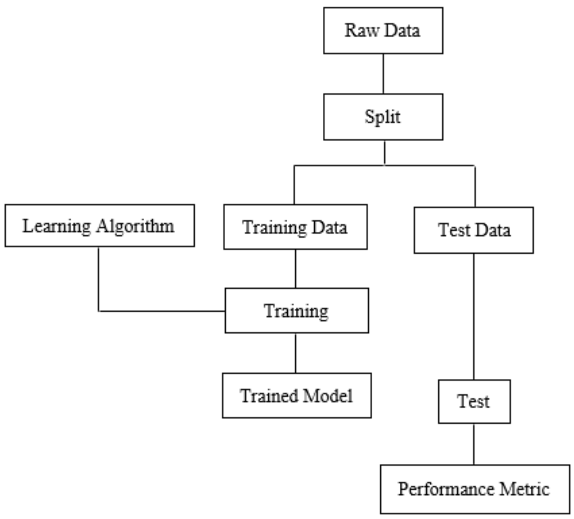
2.2. Data Preprocessing

Data preprocessing is done in order to standardize the data set. In data processing, each feature composing the data set is examined in itself. First, the average value is calculated based on a feature, and the average value is subtracted from those feature values, thus it is ensured that the average of all the values is 0. This process is called centralization. The variance of the values that make up the feature is calculated and those values are divided by the standard deviation value.

2.3. Machine Learning Algorithms

Machine learning (ML) is a subfield of artificial intelligence and consists of a number of methods that make up computer programs that automatically learn from data gained from experience (Alpaydın, 2009). There are three basic types of learning: supervised, unsupervised and reinforcement. This study uses supervised learning and the process is shown in Figure 2. The raw data are primarily divided into two subgroups, training and testing. The training data is executed using a predefined learning algorithm. After the training process, a trained model is formed. The trained model is subjected to test data, and the performance metric is calculated by calculating how true and how false it is. The learning algorithms to be used in this section are explained.

Figure 2. The flow of Supervised Learning

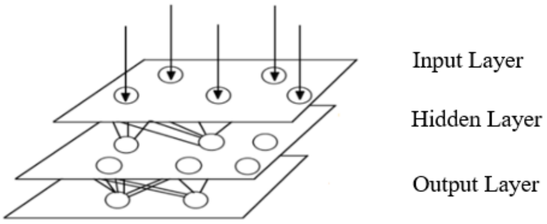


The K-nearest neighbors' algorithm (KNN) is a learning algorithm that works on the basis of the values of the nearest K neighbor. The KNN algorithm is a non-parametric method for classification and regression (Altman, 1992). It was first applied to the classification of news articles (Masand et al., 1992). When learning with the KNN algorithm, the distance between the data in the examined data set is first calculated when learning with the KNN algorithm. This length calculation is performed with a distance function (Euclidean, Manhattan, Hamming, etc.). Then the mean value of the nearest K neighbors is calculated for the data. The K value is the only hyperparameter of the KNN algorithm. If the K value is too low, the boundaries flicker and overfitting occur, whereas if the K value is too high, the separation boundaries are smoother and underfitting occurs. The disadvantage of the KNN algorithm is that it increases the processing load as the number of data increases during the distance calculation. The KNN algorithm also provides ladder like output values with far apart data point regression. In this paper, the KNN classification was used to estimate the parameters for the next year parameters. The hyperparameter K for the KNN classifier is chosen as 5.

The Random Forest (RF) method is designed as a forest consisting of more than one decision tree [24]. Each decision tree in this forest is formed as a result of selecting a sample from the data set with the bootstrap technique and randomly selecting all the variables in each decision node. The RF algorithm consists of four stages. In these stages, first of all, n features are randomly selected from a total of m features. In the second step, the d node with the best split point is calculated among the n features selected in the previous step. In the third stage, it is checked whether the final number of nodes has reached the target number. At this stage, if the final node number does not reach the target number, it returns to the first stage. However, if the final node number reaches the targeted number, the fourth stage is started and a forest is formed by repeating the steps in the first and third stages n times (Breiman, 2001; Seçkin, Seçkin, and Coşkun, 2019). In this paper, the RF classifier was used to estimate next year parameters. The number of trees which is the hyperparameter of the RF classifier is chosen as 10.

The Adaptive Boosting (AB) Algorithm is an ML algorithm called the ensemble method. With this algorithm, it is aimed to create a strong learning structure by using weak learners. The EU generally uses a one-step decision tree algorithm to detect weak learners. However, the AB algorithm consists of four stages. In the first stage, it is aimed to run N weak algorithms and learn the data set, and at this stage, 1/N weight values are assigned to N weak learning algorithms. In the second step following this step, the error value in each of the learning algorithms is calculated. In the third stage, the weight value of the algorithm is increased with a high error amount. In the fourth and last stage, the learning algorithms are collected with weights, and if the target metric limit is reached, the general algorithm output is taken, or if the targeted metric limit cannot be reached, it is returned to the second stage (Freund and Schapire 1997; Seçkin et al., 2019). In this paper, the decision tree algorithm is used as a weak learner. The number of weak learners that is the hyperparameter of AB is chosen as 100.

Figure 3. General Structure of The Artificial Neural Network



Reference: (Maind and Wankar, 2014).

In this general structure of ANN Fig. 3, some neurons are connecting outside in order to receive input and some in order to present the output. All the remaining neurons compose the hidden layers and only connect within the network. Consequently, although successful networks with a single layer can be created, networks that have an input layer, a hidden layer and an output layer are needed in general. In that process, input layer includes the neurons receiving input from outside. While the input and output layers are composed of a single layer, there may be more than one hidden layer, which include many neurons connected only to other neurons in the network, between these two layers. When a neuron in the hidden layer completes its job, it transmits its output to all the neurons of the next layer and this structure creates a feedforward path in terms of the network's output (Anderson and McNeill, 1992; Balcıoğlu et al., 2015; Detienne et al., 2003).

2.4. Machine Learning and Performance Metrics

The K-fold cross validation method is used to evaluate the performance of learning algorithms (James et al., 2013). In the application of this method, the performance of the model that updates the learning with the training data in the test dataset is tested by creating a test data set with training. However, the training and test data in the data set may not always have the same distribution, or the outliers may be differently distributed. In such cases, a reliable performance evaluation may not be possible. The K-fold cross validation method was developed for this purpose. In this method, all data is divided into K equal parts determined by the user. In this context, learning and testing was carried out for each of the K subsets by determining the K value as 20 in the study; In this context, one of the subsets is used for testing and the others for training. As a result of this method applied, performance metrics were obtained for each subset. Here, the averages of the performance metrics are considered as the performance metric of the K-fold cross-validation. A visualization of the classification performance metrics obtained through the confusion matrix is presented in Figure 4. The true positive (TP) value in a two-class confusion matrix here represents the number of predictions where the predicted value is 1 (correct) when the true value is also 1. (NS). The true negative (TN) value represents the number of predictions where the predicted value is 0 (false) while the true value is 0 (false). The false positive (FP) value represents the number of predictions where the true value is 0 (false) while the predicted value is 1 (correct). The false negative (FN) value represents the number of predictions where the true value is 1 (true) while the predicted value is 0 (false) (Seçkin and Coşkun, 2019; Seçkin et al., 2019).

$$\text{Accuracy}=\frac{\text{TN+TP}}{\text{TP+TN+FP+FN}} \tag{1}$$

Figure 4. Confusion Matrix

		Predicted	
		Positives	Negatives
Actual	Positives	True Positives (TP)	False Negatives (FN)
	Negatives	False Positives (FP)	True Negatives (TN)

3. THE RESEARCH FINDINGS AND DISCUSSION

In this study, 2020 annual probable deferred tax assets/liabilities, net deferred tax assets/liabilities, deferred tax income/expense and TAS-TFRS profit/loss values of a total of 31 companies operating in 3 different sectors (wholesale trade, retail trade and restaurants/hotels) in BIST were attempted to be estimated.

3.1. DTA Prediction Results

DTA output values are divided into three categories with the labels 0, 1 and 2. The reference ranges for these values are introduced under the title 3.1. Dataset and Properties. Accuracy performance metric comparison from the estimation results of machine learning algorithms can be seen at Table 4. Thereafter, the RF algorithm is the highest performing estimation with an accuracy rate of 0.823. The confusion matrix of the estimation results using the RF method can be seen in Figure 5. As it can be seen here, the most compared results are in sequential labels in general. That is to say, for example, while a value labelled 1 is estimated as 0 six times, the value labelled 2 is estimated as 0 twice. Since the value distribution of DTA labels can be considered equal, it can be said that the RF algorithm performs DTA estimation with a high accuracy.

Table 4. Classification Results of DTA

Machine Learning Algorithm	Accuracy
RF	0.823
ANN	0.798
AdaBoost	0.718
KNN	0.645

Figure 5. DTA Confusion Matrix for RF

		Predicted			
		0	1	2	Σ
Actual	0	48	4	2	54
	1	6	32	4	42
	2	2	4	22	28
	Σ	56	40	28	124

3.2. Net DTA Prediction Results

Net DTA output values are divided into three categories with the labels 0, 1 and 2. Accuracy performance metric comparison from the estimation results of machine learning algorithms can be seen in Table 5. Thereafter, the ANN algorithm is the highest performing estimation with an accuracy rate of 0.790. The confusion matrix of the ANN method's estimation results can be seen in Figure 6. As it can be seen here, the most compared results are in sequential labels in general. That is to say, for example, while the value labelled 1 is estimated as 0 eight times, the value labelled 2 is estimated as 0 twice. However, it is seen that the labels are not equally distributed.

Table 5. Classification Results of Net DTA

Machine Learning Algorithm	Accuracy
ANN	0.790
RF	0.764
AdaBoost	0.685
KNN	0.629

Figure 6. Net DTA Confusion Matrix for ANN

		Predicted			
		0	1	2	Σ
Actual	0	64	6	2	72
	1	8	16	4	28
	2	2	4	18	24
	Σ	74	26	24	124

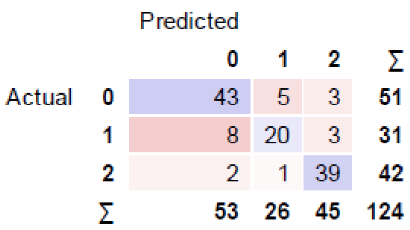
3.3. DTL Prediction Results

DTL output values are divided into three categories with the labels 0, 1 and 2. Accuracy performance metric comparison from the estimation results of machine learning algorithms can be seen in Table 6. Thereafter, the RF algorithm is the highest performing estimation with an accuracy rate of 0.823. The confusion matrix of the RF method estimation results can be seen in Figure 7. In terms of DTL estimation, labeling distribution can be considered equal and false estimation is quite rare in distant labels. Thus, it can be said that the RF algorithm provides a high success rate in DTL estimation.

Table 6. Classification Results of DTL

Machine Learning Algorithm	Accuracy
RF	0.823
ANN	0.790
AdaBoost	0.75
KNN	0.718

Figure 7. DTL Confusion Matrix for RF



		Predicted			
		0	1	2	∑
Actual	0	43	5	3	51
	1	8	20	3	31
	2	2	1	39	42
	∑	53	26	45	124

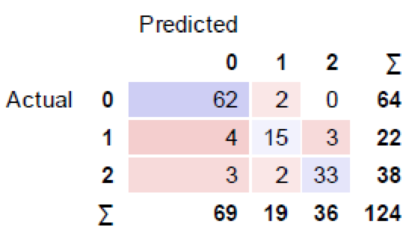
3.4. Net DTL Prediction Results

Net DTL output values are divided into three categories as 0, 1 and 2. Accuracy performance metric comparison from the estimation results of machine learning algorithms can be seen in Table 7. Thereafter, the RF algorithm is the highest performing estimation with an accuracy rate of 0.887. The confusion matrix of the RF method estimation results can be seen in Figure 8. As it can be seen here, the most compared results are in sequential labels in general. That is to say, for example, while the value labelled 1 is estimated as 0 four times, the value labelled 2 is estimated as 0 three times. Since the value distribution of net DTL value can be considered equal, it can be said that the RF algorithm performs DTA estimation with a high accuracy rate.

Table 7. Classification Results of Net DTL

Machine Learning Algorithm	Accuracy
RF	0.887
ANN	0.863
AdaBoost	0.815
KNN	0.733

Figure 8. Net DTL Confusion Matrix for RF



		Predicted			
		0	1	2	∑
Actual	0	62	2	0	64
	1	4	15	3	22
	2	3	2	33	38
	∑	69	19	36	124

3.5. Prediction Results of Deferred Tax Income/Expense due to Continuing Operations

The effect output value of deferred tax income/expense due to continuing operations is divided into three categories as 0, 1 and 2. Accuracy performance metric comparison from the estimation results of machine learning algorithms can be seen in Table 8. Thereafter, the RF algorithm is the highest performing estimation with an accuracy rate of 0.492. The confusion matrix of the RF method estimation results can be seen in Figure 9. As it can be seen here, the most compared results are in sequential labels in general. That is to say, for example, while the value labelled 1 is estimated as 0 eight times, the value labelled 2 is estimated as 0 fourteen times. However, it is seen that the labels are not equally distributed.

Table 8. Classification Results of Deferred Tax İncome/Expense Effect due to Continuous Operations

Machine Learning Algorithm	Accuracy
RF	0.492
AdaBoost	0.483
KNN	0.452
ANN	0.419

Figure 9. Deferred Tax İncome/Expense Effect due to Continuous Operations Confusion Matrix for RF

		Predicted			
		0	1	2	∑
Actual	0	25	3	13	41
	1	8	8	16	32
	2	14	9	28	51
	∑	47	20	57	124

3.6. TAS-TFRS Profit/Loss Prediction Results

TAS-TFRS profit/loss output values are divided into three categories as 0, 1 and 2. Accuracy performance metric comparison from the estimation results of machine learning algorithms can be seen in Table 9. Thereafter, the RF algorithm is the highest performing estimation with an accuracy rate of 0.629. The confusion matrix of the RF method estimation results can be seen in Figure 10. As it can be seen here, the most compared results are in sequential labels in general. That is to say, for example, while a value labelled 1 is estimated as 0 six times, the value labelled 2 is estimated as 0 six times. However, it is seen that the labels are not equally distributed.

Table 9. Classification Results of TAS-TFRS Profit/Loss

Machine Learning Algorithm	Accuracy
RF	0.629
ANN	0.532
KNN	0.524
AdaBoost	0.5

Figure 10. TAS-TFRS Profit/Loss Confusion Matrix for RF

		Predicted			
		0	**1**	**2**	**Σ**
Actual	**0**	19	5	9	**33**
	1	6	23	10	**39**
	2	6	10	36	**52**
	Σ	**31**	**38**	**55**	**124**

3.7. 2020 Prediction Results

The estimated results of the 2020 deferred tax and TAS/TFRS profit/loss values of the companies examined in the study are presented in Table 10 below. According to Table 10, it is seen that most successful algorithms in estimations are as follows; RF with an accuracy value of 0.823 for DTA value, ANN with an accuracy rate of 0.790 for net DTA value, RF with an accuracy rate of 0.823 for DTL value and RF with an accuracy rate of 0.887 for net DTL value. It can be seen that the most successful algorithm for the future estimation of DTIECO value is the RF with an accuracy rate of 0.492. For TAS-TFRS P/L value, the most successful algorithm is the RF with an accuracy rate of 0.629. When the prediction results are evaluated in terms of each output parameter, it is predicted that in terms of DTA and net DTA values, Intema and Selçuk companies (with their abbreviated company names) in the wholesale trade sector will report more DTA and net DTA within the range of category 2 compared to other companies in the same sector. Carrefoursa and Şok companies (with their abbreviated company names) in the retail trade sector are predicted to report more DTA and net DTA within the category 2 compared to other companies in the same sector. And for the restaurants and hotels sector, it is predicted that Martı will report more DTA and net DTA within the category 2 compared to other companies in the same sector. Thus, we can say that those companies who are estimated to have more DTA value compared to other companies in the sector will have more tax advantage in the future.

When the companies are evaluated by their future DTL values; Sanko and Selçuk in wholesale trade, Milpa and Mepet in retail trade, Altınyunus, Avrasya, Tek-Art and Utopya in restaurants and hotels sectors are predicted to be reporting higher DTL values and in the category 2. It can also be said that, because of the DTL values to be reported by these companies, they will have more tax liability next year compared to others in the sector.

When the companies are evaluated by their Net DTL prediction results; Sanko in wholesale trade, Mepet, Milpa and Vakko in retail trade, Altınyunus, Avrasya, Tek-Art and Utopya in restaurants and hotels sectors are predicted to be reporting more DTL and in the category 2.

When the companies are evaluated by their DTIECO prediction results; Doğuş, İntema, Selçuk and Uzertaş in wholesale trade, Carrefoursa, Casa and Şok in retail trade, Martı and Ulaşlar in restaurants and hotels sectors are predicted to be reporting higher deferred tax expense in the category 2, thus reducing the total tax revenues the government will collect. It is estimated that all other companies in the sector will report deferred tax income in the categories 0 and 1, thus increasing the total tax revenues the government will collect.

When the companies are evaluated by their TAS-TFRS profit/loss values; Doğuş, Metal and Uzertaş in wholesale trade, Adese, Carrefoursa, Mepet, Şok and Teknosa in retail trade, Altınyunus, Etiler, Martı, Metemtur, Tek-Art, Ulaşlar and Utopya in restaurants and hotels sectors are predicted to be reporting TAS-TFRS loss in the category 2 next year. All the other companies in the sector are estimated to report TAS-TFRS profit in the categories 0 and 1.

Table 10. Estimated Categorical Ranges of 2020 Deferred Taxes and TAS-TFRS Profit/Loss Calculated with the Most Successful Algorithms

Company	Company code	Sector	DTA	Net DTA	DTL	Net DTL	DTIECO	TAS-TFRS K/Z
			RF	ANN	RF	RF	RF	RF
Doğuş	DOAS	Wholesale	1	0	0	0	2	2
İntema	INTEM	Wholesale	2	2	0	0	2	1
Metal	METAL	Wholesale	1	1	0	0	0	2
Pergamon	PSDTC	Wholesale	1	1	0	0	0	1
Sanko	SANKO	Wholesale	0	0	2	2	1	1
Selçuk	SELEC	Wholesale	2	2	2	0	2	1
TGS	TGSAS	Wholesale	1	1	0	0	0	1
Uzertaş	UZERB	Wholesale	1	0	1	1	2	2
Adese	ADESE	Retail	1	0	1	1	0	2
Bim	BIMAS	Retail	1	0	1	1	0	0
Bizim	BIZIM	Retail	1	0	0	0	0	1
Carrefoursa	CRFSA	Retail	2	2	0	0	2	2
Casa	CASA	Retail	0	0	1	1	2	1
Mavi	MAVI	Retail	1	0	1	0	0	0
Mepet	MEPET	Retail	0	0	2	2	1	2
Migros	MGROS	Retail	0	0	1	1	0	0
Milpa	MIPAZ	Retail	0	0	2	2	1	1
Şok	SOKM	Retail	2	2	0	0	2	2
Teknosa	TKNSA	Retail	1	1	0	0	0	2
Vakko	VAKKO	Retail	0	0	1	2	0	1
Altın Yunus	AYCES	Restaurants and Hotels	0	0	2	2	0	2

Avrasya	AVTUR	Restaurants and Hotels	0	0	2	2	0	1
Etiler	ETILR	Restaurants and Hotels	1	0	0	0	0	2
Kuştur	KUSTUR	Restaurants and Hotels	0	0	1	1	0	1
Marmaris	MAALT	Restaurants and Hotels	0	0	0	0	0	1
Martı	MARTI	Restaurants and Hotels	2	2	0	0	2	2
Merit	MERIT	Restaurants and Hotels	1	0	1	0	0	1
Metemtur	METUR	Restaurants and Hotels	1	0	0	0	2	2
Tek-Art	TEKTU	Restaurants and Hotels	0	0	2	2	1	2
Ulaşlar	ULAS	Restaurants and Hotels	1	0	0	0	2	2
Utopya	UTPYA	Restaurants and Hotels	0	0	2	2	1	2

4. CONCLUSION

The translation of IAS/ IFRS to Turkish as TAS/TFRS and their adoption in Turkish accounting practices have revealed certain temporary differences between the existing accounting practices and accounting standards resulting from timing and valuation. With this study, using the machine learning method, it is aimed to estimate the next year's temporary differences of 31 companies in wholesale trade, retail trade and restaurants/hotels sectors based on the values in their financial reports for the 2015-2019 period as well as twelve main economic parameters. Estimated future values were obtained by using the artificial neural networks, the Random Forest, the KNN and the AdaBoost methods as part of machine learning. In this context, when the companies are evaluated in terms of their future DTA and net DTA values, İntema and Selcuk (with their abbreviated company names) in the wholesale trade sector; Carrefoursa and Şok (with their abbreviated company names) in the retail trade sector and Martı (with its abbreviated company name) in the restaurant and hotels sector will report more DTA and net DTA within the category 2 compared to other companies in the same sector. Thus, it can be said that these companies will benefit from high tax advantage next year. As a result of the study, it was concluded that the deferred tax values for the next year are estimated with a high success rate using the classification method in machine learning. In addition, the categorical results of the deferred tax values and the TAS-TFRS profit/loss values which are predicted for each sector are tabulated with the most successful algorithms.

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