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# Financial Forecast in Business and an Application Proposal: The Case of Random Forest Technique[*]

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***ABSTRACT***

*The financial forecast is a subject that investors and researchers have been working on for many years. The developing business environment and the globalising market have led to many variables. This situation has led to the complexity of forecasting models. Technological developments have enabled financial forecasts to be made by computer programs. This way, it has been possible to analyse with more variables and avoid mistakes. In this study, five businesses from different sectors whose shares are traded in Borsa Istanbul were randomly selected. The financial statements of these businesses between 2009 and 2020 were obtained from the Public Disclosure Platform website. Current assets, fixed assets, equity, net sales, and net profit items of the businesses between 2010 and 2020 are forecasted using the random forest technique. As a result of the research, it has been determined that the random forest technique can be used effectively in the financial forecast.*

***Keywords:*** *Financial forecast, random forest, machine learning, financial analysis, financial estimation.*

***Jel Classification****:M40, M41, G47*

***İşletmelerde Finansal Kestirim Ve Bir Uygulama Önerisi: Rassal Orman Tekniği***

***ÖZET***

*Finansal kestirim, uzun yıllardır yatırımcıların ve araştırmacıların üzerinde çalışmalar yaptığı bir konudur. Gelişen işletme çevresi ve küreselleşen piyasa birçok farklı değişkenin ortaya çıkmasını sağlamıştır. Bu durum da tahmin modellerinin karmaşıklaşmasına yol açmıştır. Teknolojik gelişmeler, finansal kestirimin bilgisayar programları tarafından yapılmasına olanak sağlamıştır. Bu sayede, hem daha fazla değişken ile analiz yapma hem de hatalardan kaçınma imkânı doğmuştur. Bu çalışmada, hisseleri Borsa İstanbul'da işlem gören farklı sektörlerden beş işletme seçilmiş ve söz konusu işletmelerin 2009-2020 yılları arası finansal tabloları Kamuyu Aydınlatma Platformu web sitesinden edinilmiştir. İşletmelerin 2010-2020 yılları arası; dönen varlıklar, duran varlıklar, özkaynaklar, net satışlar ve dönem net kârı kalemleri rassal orman tekniği kullanılarak tahmin edilmiştir. Yapılan araştırma sonucunda, rassal orman tekniğinin finansal kestirimde etkin bir şekilde kullanılabileceği tespit edilmiştir.*

***Anahtar Kelimeler:*** *Finansal kestirim, rassal orman, makine öğrenmesi, finansal analiz, finansal tahminleme.*

***JEL Sınıflandırması:*** *M40, M41, G47*

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## 1. INTRODUCTION

Businesses' primary purposes are to serve society, survive, and increase the shareholders' welfare by making a profit. In today's high competition and globalising market, it has become difficult for businesses to fulfil these three goals. The fact that the decisions taken in the organisations are in an environment of uncertainty and risk can cause both the inability to evaluate new investment opportunities effectively and the failure of investments. Making forecasts for the future in businesses to reduce uncertainty and risk is a subject that has been studied for many years.

It has been known that the financial forecast is used by investors, lenders, business owners, and partners. Investors want to know the future financial status and financial performance of the businesses they channel their savings, and lenders want to know the financial performance of the businesses they fund. Besides traditional financial analysis techniques, statistical models and machine learning techniques can also be used for this purpose.

Machine learning techniques in financial forecasting in the 2000s have also emerged in estimating financial failure. For this purpose, studies in which machine learning techniques such as neural networks, logistic regression, and probit have frequently been encountered in the literature.

## 2. THE CONCEPT OF FINANCIAL FORECAST

Forecast is defined as predicting an event, something that may happen based on reason, intuition, or some data, is also referred to as a forecast. According to this definition, for an idea to be considered a forecast, it must first be based on logical data, and a prediction must also be made about an event that may occur in the future.

By evaluating the data at hand, forecasts can be made in all areas of life, as well as forecasts about the future financial status and financial performance of businesses. The future profit margins of the businesses, the changes that will occur in the asset and resource structure, and the changes that will occur in the sales or costs can be predicted using the correct data and the proper analysis techniques.

The businesses' financial statements are undoubtedly the most critical data to forecast future financial status and financial performance. The purposes of organising financial statements can be listed as follows. (Sağlam,2020:57)

- To provide helpful information in the decisions to be taken by people who are interested in the business, such as investors, lenders,
- To provide helpful information in the evaluation of future cash flows,
- To provide helpful information about the asset-resource structure of the business, the changes, and the business's operations results.

The financial forecast is an essential factor that affects people's decisions outside and inside the business. The primary benefit of financial forecasting is to support planning within the business and making decisions to invest or lend to the business outside the business.

Considering the internal and external decision-makers, the financial forecast results are effective on the decisions of managers, partners, investors, and lenders. Managers can predict how the business's future financial position and financial performance will be affected due to making an investment or using a financing opportunity through the financial forecast.

Partners can see the results of the responsibilities and authority they give business managers through financial reports. The effect of these results on the future can be estimated as a result of the financial forecast.

Potential investors want the future financial situation and financial performance of the business to be predictable, as well as the business's current financial situation and financial performance, in the investment decisions, they will make regarding the business. Investors may aim to earn dividends in the long term or generate income in the short term by taking advantage of stock price changes. In both cases, investors have to make assumptions about the future. In this context, the financial forecast ensures that the decisions to be taken by investors are more effective and safe.

Forecasting financial failures in terms of loan repayment are significant for lenders. Dead loans cause a contraction in the money market and prevent banks from continuing their activities efficiently. This situation adversely affects the lenders, the other businesses needing loans, and the country's economy. In this context, financial forecast supports lenders in the following areas: (Bodur-Teker,2005:26)

- The financial position of the business at the time the financial statements are issued,
- Whether the debt solvency is sustainable,
- Whether the financial performance from the past will continue in the future,
- Whether it can raise sufficient funds to repay the loan requested.

It has been seen that financial forecast techniques are also used in the independent auditing of financial statements. In independent audit applications, the historical financial data of the businesses are examined. However, today, businesses and users of financial information care about the reliability of prospective and historical financial information. As a result of all these requirements, “Assurance Engagements” applications, which refer to audit services other than independent auditing and limited auditing, have started. (Dinç ve Atabay,2016:1527)

International Standard on Assurance Engagements (ISAE) are included in the second chapter of the 2018 Handbook of International Quality Control, Auditing, Review, Other Assurance, and Related Services Pronouncements, edited by The International Auditing and Assurance Standards Board (IAASB) and published by The International Federation of Accountants (IFAC). ISAE 3400 “The Examination of Prospective Financial Information” and ISAE 3420 “Assurance Engagements to Report in the Compilation of Pro Forma Financial Information Included in a Prospectus” was translated into Turkish by the Turkish Public Oversight Accounting and Auditing Standards Authority and published within the scope of Turkey Auditing Standards (TDS).

In ISAE 3400, the projection has been defined as “prospective financial information prepared based on hypothetical assumptions or a combination of best estimate and hypothetical assumptions regarding future events and management actions that are not expected to occur with certainty".

The proforma financial information has been defined as "financial information presented with adjustments made to show the effect of a material event or transaction on the unadjusted financial information of the entity as if it were an event that occurred or a transaction undertaken at a previous date selected for this purpose" in GDS 3420.

## 3. LITERATURE REVIEW

It has been determined that the studies on the financial forecast mainly estimate the stock market price or predict the risk of financial failure in the literature reviews. It has been seen that the first studies on financial forecasting were studies on predicting business failures. In the literature, there are financial forecast studies using statistical and machine learning techniques. The main studies using statistical techniques are listed below.

Beaver (1966) collected 30 financial ratios under six groups in his study and applied a single discriminant analysis for each ratio. As a result of the study, he determined that the cash flow/debt total ratio can be used to predict financial failure.

Altman (1968) examined the financial ratios of 66 manufacturing enterprises with the multiple discriminant analysis method and developed the Z-Score model, which consists of five ratios that can be used to predict financial failure. As a result of the research, it has been identified that Working capital/Total assets, Retained Earnings/Total assets, Earnings before interest and taxes/Total assets, Market value equity/Book value of total debt, and Sales/Total assets ratios were distinctive in predicting business failures.

Springate (1978) examined the financial ratios of 40 businesses using discriminant analysis to predict the financial failures of businesses operating in Canada and developed a model that provides a 92.5% successful classification in estimating business failures.

Rose, Andrew, and Giroux (1982) examined 28 macroeconomic indicators that could affect the failure of businesses and revealed that unemployment and interest rates were highly influential in the financial failures of businesses.

Terzi (2011) examined 19 financial ratios obtained from the financial statements of 22 businesses operating in the food industry with the discriminant analysis method. In measuring financial failure for businesses operating in the food industry, it was found that six ratios showed a significant difference between businesses that were unsuccessful financially and businesses that were not financially unsuccessful.

In their study, Bagheri, Peyhani, and Akbari (2014) aimed to develop a hybrid smart method to predict financial time series, especially in foreign exchange markets. In the method, which was intended to be used to predict market trends, both historical market data and chart patterns were used. It was concluded that the presented hybrid method was useful and effective for financial price estimation and financial model extraction.

Kulalı (2016) aimed to measure the effectiveness of the Altman Z Score model in predicting financial failure in businesses. In the study, the financial data of 19 bankrupt businesses whose shares were traded in Borsa Istanbul between 2000 and 2013 were used, and it was determined that the prediction power of the Altman Z Score model was still relatively high.

As a result of technological developments and scientific advances, machine learning techniques have started to be used in studies. Some studies using machine learning techniques are listed below.

Mahfoud and Mani (1996) aimed to present a new system that uses genetic algorithms to predict the future performance of stocks. The genetic algorithm system was compared to a neural network system using the results of over 1600 stocks and approximately 5000 experiments. As a result of the comparison of the two methods, it was determined that the genetic algorithm system performed significantly better.

Atiya (2001) analysed 120 different financial ratios using the neural network method, and the model he developed provided a classification success between 81% and 89%.

Enke and Thawornwong (2005) examined data mining and neural network techniques used to determine financial and economic variables with the ability to predict forward. It was concluded that trading strategies guided by linear regression and neural network models produce safer decisions than trading strategies.

In their study, Ege and Bayrakdaroğlu (2009) aimed to predict stock return performances using the logistic regression method. As a result of the analysis using 20 financial ratios and nominal TL returns obtained from the 2004 financial statements of the businesses on the ISE 30, it was determined that the Price/Earnings Ratio, Cash Ratio, and Total Assets Turnover Rate ratios had a significant relationship with the stock yield. It was concluded that the market value/book value ratio did not have a significant relationship with the stock yield.

Lin (2009) compared the classification success of multiple discriminant analysis, logit, probit, and neural network techniques in measuring financial failure using 20 financial ratios. He found that the logit method showed better classification success.

Kurtaran Çelik (2010) compared discriminant analysis and neural network methods in measuring financial failure in his study. The financial ratios of 36 privately owned banks were examined with these two methods, and it was determined that the neural networks for one year before the financial failure and the discriminant analysis method for two years before the financial failure showed a more successful classification performance.

In the study conducted by Penman (2010), financial foresight, risk detection, and valuation issues were examined. In this descriptive study, related issues were discussed in detail within the scope of accounting literature.

Ünvan and Tatlıdil (2011) analysed the financial ratios of banks operating in Turkey between 2002-2008 using logit, probit, and discriminant analysis methods. As a result of the study determined that the most appropriate method for the analysis using a priori data for the sector in question was discriminant analysis.

In the study conducted by Kazem et al. (2013), a prediction model based on chaotic mapping, firefly algorithm, and support vector regression was proposed to predict stock market price. The developed model's results were compared with those obtained from ANFIS, CHAOS, and models. It was concluded that the results of the developed model were more consistent than other models in the analysis of the relations between inputs and outputs.

Altunöz (2013) used the neural network method to measure the financial failure risk of banks in his study. In the study conducted on 36 financial ratios of 36 privately owned banks, a forecasting model was developed for one and two years before the financial failure. The model, as mentioned earlier, showed a classification success of 88% for one year before the financial failure and 77% for two years before the financial failure.

The study by Özkan and İnal (2014) aimed to adapt the neural networks technique to the Fuzzy approach and compare ANFIS applications in solving multi-criteria decision-making problems. As a result of the analysis, it was determined that the ANFIS model created more consistent results.

Jareno, Valero, and Pavia (2017) aimed to measure the effectiveness of artificial intelligence applications in the detection of accounting fraud in their study. As a result of the analysis of 600 businesses' financial statements, it was determined that the random forest technique gave better results with the SMOTE transformation. In terms of technical cheating, it showed a classification success of 96.15% in positive outcomes and 94.98% in adverse outcomes.

Rustam and Saragih (2018) used the random forest technique in their study to predict bank financial failures that emerged due to the economic crisis in Turkey in the 1994-2004 period. While the random forest technique showed 94% classification success when there were 20 financial ratios in the analysis data set, the classification success was calculated as 96% in the analyses with six financial ratios.

Xuan et al. (2018) analysed the data they received from an e-commerce company operating in China using two different random forest models and compared their success in detecting credit card fraud in their study. In the analysis, it was concluded that the classification success of the random forest technique was high. Still, the assumption that each of the basic classifiers had equal weight limits the potential success of the method.

Jabeur and Fahmi (2018) searched the effectiveness of discriminant analysis, logistic regression, and random forest techniques in predicting financial failure. Thirty-three financial ratios obtained from the financial statements of the businesses in question between 2006-2008 were used in the analyses made on a sample of 800 businesses consisting of 400 healthy and 400 unsuccessful businesses. As a result of the analyses, it was determined that the technique with the highest classification success was random forest by minimising type 1 and type 2 errors.

In their study, Fischer and Krauss (2018) compared the classification success of machine learning techniques to predict out-of-sample directional movements of S&P 500 stocks from 1992 to 2015. The study compared LSTM algorithm, random forest, deep neural networks, and logistic regression techniques. As a result of the analysis, the LSTM algorithm showed the most successful classification, while the random forest technique showed the highest classification success among memoryless classification methods.

Glosh, Sanyal, and Jana (2018) used a machine for experimental research and predictive modelling on daily index prices of the Mumbai stock market, Dow Jones Industrial Average, Hang Seng Index, NIFTY 50, NASDAQ and NIKKEI, which represent developed and emerging economies. They used learning techniques. Adaptive neuro-fuzzy inference system, dynamic evolving neuro-fuzzy inference system, Jordan neural network, support vector machines, and random forest techniques were used to forecast future index prices. The analysis concluded that predictive models could be used effectively for portfolio creation and rebalancing.

Nami and Shajari (2018) aimed to create a model to prevent credit card fraud by using dynamic random forest and k-nearest neighbour techniques in their study. It was determined that the developed model would contribute 23% to the prevention of losses caused by credit card fraud.

Weber et al. (2019) examined machine learning techniques to prevent the use of cryptocurrencies in money laundering processes. Logistic regression, random forest, multi-layer perceptrons, and graphical convolutional network techniques were used in the study, which was conducted with a large, labelled dataset obtained from the AML (Anti-Money Laundering) community, never publicly available. As a result of the analysis, it was determined that the technique with the highest classification success was the random forest technique.

In their study, Lee et al. (2019) searched the use of machine learning techniques in global capital market investment strategies. In analyses using logistic regression, support vector machines, and random forest techniques, the techniques had to be critical complementary indicators in predicting global and regional stock market movements (up/down).

İşgüden Kılıç (2019) defined big data analysis techniques and technologies that come to the fore in the fields of accounting, finance, and auditing in his study. The study discussed and defined the random forest technique among the supervised learning techniques, one of the big data analysis techniques.

In their study, Xiong et al. (2019) combined the random forest technique with the k-fold cross-validation system and developed the k-fold random forest algorithm to establish the financial early warning indicator selection method created with machine learning techniques. As a result of the comparison, it was determined that the proposed model increased the success of the random forest technique.

In the literature search, no study was found on forecasting the amounts of financial statement items in future years using machine learning techniques.

### 4. SCOPE AND METHODOLOGY OF THE RESEARCH

#### 4.1. Scope

In this study, five businesses from different sectors whose shares have been traded in Borsa Istanbul were selected, and the financial statements of these businesses between 2009 and 2020 were obtained from the Public Disclosure Platform website. Between the years 2010-2020, the enterprises; Current assets, fixed assets, equity, revenue, and net income items have been estimated by use of the random forest technique.

#### 4.2. Methodology

The random forest consists of a combination where each tree generated using a random vector sampled from the input vector cast a unit vote for classification (Pal,2007:218). The random forest technique developed by Breiman (2001) is an estimation system in which each decision tree depends on the values of an independently sampled random vector, and all decision trees in the forest have the same importance.

Random forest is a supervised machine learning algorithm. The forest created in this technique usually consists of decision trees trained by the "bagging" method. The bagging method is used to increase the overall result with a combination of learning models (Gültepe,2019:10).

There are many decision trees in the random forest technique, and each decision tree has an equal weight. The predictions of all decision trees are combined, and the most repeated forecasts are considered as valid. The technique has higher predictive power than a single decision tree. At the same time, the generalisation error due to the correlation between the decision trees is also lower.

Random forest is frequently preferred in classification and regression analyses because it produces reliable results by using the average of more than one decision tree and allows working with any number of trees (Biau-Scornet,2016:198). In the random forest technique, the model can be built using the entire data set. In addition, the model can also be established by separating the data set into test and train data. For the random forest forecast model, “n” resampling samples are selected at first. Some of the selected samples are used as training data and the rest as train data, and classification and regression trees (CART) are generated for each resampling sample. From the learning data set, “m” random samples are selected to determine the variable that will provide the best splitting. By combining the forecast of “n” decision trees, a new data set is estimated by considering the average in the regression analyses and the majority of votes in the classification analyses. As a result, the result produced by the cluster with the highest number of votes is determined as the result of the study (Akman-Genç-Ankaralı,2011:38).

In the random forest technique, the steps to create the forecast model are performed in the following order (Afanador et al.,2015:232-233):

- Step 1: We start with a data set of size “n” consisting of a set of estimators and a response variable.

- Step 2: With the resampling method, “n” number of samples are determined from the data set.
- Step 3: Starting from the first node of each tree in the forest and at each subsequent node, “m” estimators are randomly sampled.
- Step 4: With the decision trees created without including the forecast variables, the forecast variables are determined.
- Step 5: The forecast and forecast error of all “t” trees are summed, and forecast success is evaluated.

Random forest algorithm contains certain parameters. These parameters are listed as follows (Liaw-Wiener, 2002:18):

- Forecast variables and response variables as train data,
- Number of decision trees,
- The number of forecast variables for the binary rules of each distinction or decision,
- Error and variable significance calculation parameters.

Some of the variables included in the analysis have a significant impact on the classification or forecast results, while others are of low importance. In order for the classification or prediction model to be successful, it is essential to determine the importance levels of the variables, and the random forest technique is successful in this regard. By determining the significance levels of the variables, it is possible to exclude variables that provide less information to the analysis from the data set, and the model can be rerun without these variables. In addition, outliers in the learning data that differ from the other data in the class they belong to can be evaluated with the random forest technique. Thus, classes with outliers can be identified, and the learning data set can be revised (Horning,2010:4).

In the random forest technique, the best classifier among the branches of the decision trees is determined by the Gini Index. The Gini Index is expressed as follows: "T” refers to the learning dataset and “Ci” refers to the class to which the data belongs.

$$\sum \sum_{j \neq i} (f(C_i, T)/|T|)(f(C_i, T)/\lceil T \rceil)$$

The random forest technique, which shows high forecast success, is frequently used in decision support systems in social sciences. On the other hand, it has been seen that the random forest technique has not been used in the forecast studies of financial statements in the literature review. This study aims to search for the effectiveness of the random forest technique in estimating the size of financial statement items in the future. The basic random forest structure is shown in Figure 1.

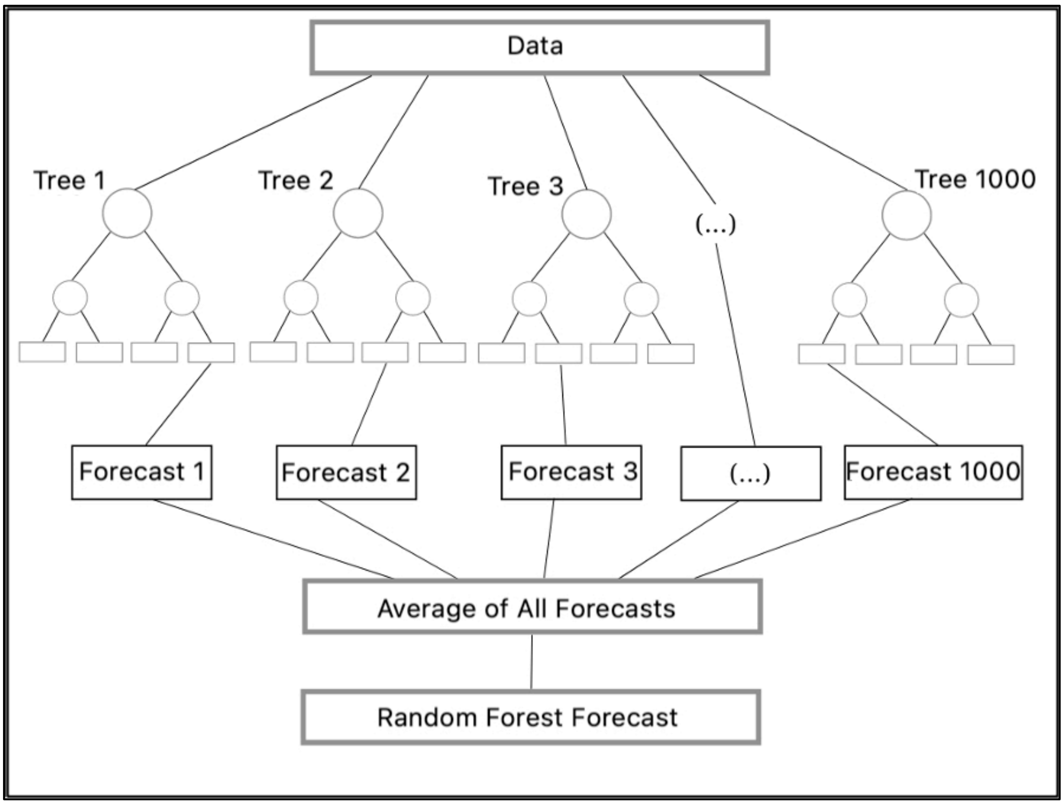


**Figure 1.** Main Structure of Random Forest (Araya, et al.,2017:193).

In the analysis, in addition to the data obtained from the financial statements of the enterprises, the economic indicators of the years when the financial statements were prepared are also included in the data set. The macroeconomic variables included in the analysis are as follows:

- US Dollar Rate
- Inflation Rate,
- Unemployment Rate,
- Minimum Wage Increase Rate,
- Gross Domestic Product Growth Rate,
- Central Bank of the Republic of Turkey (CBT) Interest Rate.

It has been known that the macroeconomic variables mentioned above affect many factors, such as sales price, sales amount, production cost, production amount, size of operating expenses, size of financing expenses, employment policy, and credit sales policy.

It has been known that changes in exchange rates affect stock items such as raw materials and materials in industry and service enterprises and commercial goods in trade enterprises. Price changes in these items affect the total current assets, sales price, gross profit, and, therefore, net profit of the enterprises (Doğanay,2016:151). Considering this situation, the US Dollar rate, one of the most frequently used exchange rates, was used as a variable in the analysis.

Stocks such as inflation rate and exchange rate affect gross and net profit items. The revaluation rate determined by the Turkish Ministry of Treasury and Finance is used for many elements, such as rent increases and renewal contracts every year. In addition, the revaluation rate is also used to determine the increases in the amounts of many taxes, duties, fees, valuable paper costs, and traffic fines. The revaluation rate represents the average price increase in the Producer Price Index (PPI) from October of the previous year to October of the year to be revalued (Karakoç,2020:251).

Inflation also affects the asset and resource structure of businesses. In accordance with the "IAS 29 Financial Reporting in Hyperinflationary Economies" standard, non-monetary items on the balance sheets of businesses during periods of high inflation are adjusted using a general price index. According to IAS 29, hyperinflation is determined by a country's economic characteristics, including but not limited to as follows:

a) The majority of the population prefers to keep their wealth in non-monetary assets or a relatively stable foreign currency. Local currency held is evaluated by direct investment etc., to maintain its purchasing power.
b) The majority of the population considers monetary amounts in a relatively stable currency, not in local currency. Prices can also be determined in this currency;
c) Prices in sales and purchases on credit are determined to cover expected losses in purchasing power over the loan term, even if the term is short;
d) Interest rates, wages, and prices depend on a 'price index'; and
e) The cumulative inflation rate of the last three years is approaching or exceeding 100%.

The unemployment rate has been included in the analysis with the assumption that it affects the direct labour and indirect labour costs of the enterprises. In this context, it affects the cost of production of products and services.

It has been known that the rate of minimum wage increase directly affects workers' wages and expenses. Considering that worker wages and expenses also affect the cost of goods sold, services sold, and operating expenses, this variable has been included in the analysis.

It has been known that the Gross Domestic Product growth rate is used in purchasing power parity calculations. Like the exchange rate, purchasing power parity also affects inventory items such as raw materials and commodities. The increase in the prices of the inventories affects the production costs, the cost of sales, and the sales price (Petek-Şanlı,2019:51).

CBT Interest Rate is used in many transactions, such as determining loan interest rates, calculating the maturity difference in forward sales, and rediscount calculations. This situation affects many financial statement items such as sales revenues, financing expenses, profit before tax, and net profit of businesses (Demir,2010:40). Considering this situation, the mentioned variable has been included in the analyses.

In the analysis, a total of 113 variables were used in the research, separately for each business. Name similarities in financial statement items can cause errors in the analysis. For example, the "Trade receivables" item is included in both current and non current assets.

Similarly, the “Bank Loans” item is included in both short-term and long-term liabilities. To avoid errors like this, a code is assigned to all variables.

The data set of the application consists of the financial statements of five businesses selected from different sectors, whose shares were traded in Borsa Istanbul between the years 2009-2020 and the macroeconomic variables in the same years.

The businesses included in the analysis were determined by the purposive sampling method, one of the non-probability sampling methods. To carry out the research in-depth, the selection of data sources rich in information in line with the purpose of the study is called purposeful sampling (Büyüköztürk,2012:9). While determining the sample mass, appropriate criteria were taken as a basis. According to this, businesses operating in the industry, production of durable consumer goods, health, fuel, and retail trade sectors, whose 11-year financial data can be accessed, were preferred. The businesses whose financial data for 11 years can be accessed and included in the analysis in the selected sectors are as follows:

- Afyon Çimento Inc.
- Arçelik Inc.
- Lokman Inc.
- Mepet Inc.
- Migros Inc.

The 3.8.5 version of WEKA software was used to analyse the data. WEKA “Waikato Environment for Knowledge Analysis” software was developed at the University of Waikato to apply machine learning techniques. The software includes the vast majority of machine learning algorithms used today. The software is open source, has a modular design, and is distributed under the GPL General Public Licence. So it is convenient for accessing and customising.

WEKA can read data from files in arff, csv, and c4.5 formats. It is also possible to perform transactions by connecting to the database via JDBC. WEKA also includes data processing, classification, clustering, and association features.

Dener, Dörterler, and Orman (2009) determined that WEKA was the most used data mining program. At the same time, in the preliminary analyses made by us using the WEKA and Phyton software, it was determined that the WEKA software made more consistent predictions, and it was decided to use the WEKA software in the analysis.

## 5. RESULTS

In the conducted random forest technique, an algorithm consisting of 1000 decision trees was used for each forecast model. The weights of the data in the model were not interfered with in any way, and it was ensured that the data were learned by the program with the supervised learning technique. For each forecasted variable, the data from all previous years were used as train data. For example, while estimating the revenue amount of 2018, all variables between 2009-2017 were used as train data, and when estimating the revenue amount of 2019, all variables between 2009-2018 were used as train data. Random forest models consisting of 1,000 decision trees were used for each forecast.

**Table 1.** Success Rates of Afyon Çimento Financial Forecast

| Year | Revenue | Net Income/Loss | Current Assets | Fixed Assets | Equity | Gain/Loss Direction |
|---|---|---|---|---|---|---|
| 2010 | 91,80% | 57,23% | 89,89% | 80,07% | 78,14% | Linear |
| 2011 | 92,42% | 77,32% | 86,01% | 76,12% | 87,38% | Linear |
| 2012 | 82,75% | 94,72% | 91,67% | 60,11% | 76,79% | Linear |
| 2013 | 99,02% | 75,85% | 69,99% | 65,55% | 71,96% | Linear |
| 2014 | 92,62% | 75,06% | 92,83% | 66,83% | 78,25% | Linear |
| 2015 | 91,32% | 80,35% | 88,75% | 57,92% | 81,81% | Linear |
| 2016 | 67,68% | 73,55% | 55,55% | 86,45% | 93,95% | Linear |
| 2017 | 96,75% | 75,89% | 87,62% | 94,74% | 99,53% | Linear |
| 2018 | 99,99% | 92,06% | 99,01% | 99,07% | 96,62% | Linear |
| 2019 | 97,55% | 91,99% | 87,28% | 96,79% | 84,25% | Linear |
| 2020 | 81,91% | 95,22% | 42,11% | 99,38% | 98,23% | Linear |
| **Average** | **90,35%** | **80,84%** | **80,97%** | **80,27%** | **86,08%** | **100%** |

5,504 for revenue, 5,962 for net income or loss, 5,140 for current assets, 5,880 for fixed assets, and 5,252 nodes for equity were used in random forest models, each of which consists of 1,000 decision trees.

The average success of the forecasts made regarding the revenue amount of the business was calculated as 90.35%. The highest success in the forecast for the revenue amount was achieved in 2018, with 99.99%. The highest deviation in the forecasts was observed in the estimates for 2016. The forecast success in 2016 remained at the level of 67.68%. The technique showed a forecasting success of over 90% in 8 of 11 years and between 80% and 90% in two years.

The average success rate of the forecasts regarding gain or loss amounts was 80.84%. While the lowest forecasting success was shown in 2010 with 57.23%, the highest forecasting success was achieved in 2020 with 95.22%. However, the business's gain or loss forecast in the relevant year was made correctly in all years, and 100% success was achieved in this forecast.

When the estimated amounts for the current assets item were compared with the actual amounts, the average forecast success of the technique was calculated as 80.97%. While the highest forecasting success was realised in 2018 amounts, the highest deviation was in 2020 amounts, with 42.11% forecasting success.

While the total fixed assets of the enterprise were estimated to be 99.38% successful in 2020, this rate remained at 57.92% in 2015. The overall forecast success was calculated as 80.27%. Although the technique forecasted an increase in fixed assets in 2015, the increase in fixed assets was much higher than expected.

The forecasting success of the technique in the equity item reached the highest level in 2017, with 99.53%. The year with the highest deviation in forecasts was 2013, with a forecasting success of 71.96%. The fact that significant changes in equities in 2015 and 2020 were largely forecasted stands out as a positive indicator from a technical point of view.

**Table 2.** Success Rates of Arçelik Financial Forecast

| Year | Revenue | Net Income/Loss | Current Assets | Fixed Assets | Equity | Gain/Loss Direction |
|---|---|---|---|---|---|---|
| 2010 | 83,17% | 97,53% | 79,16% | 85,65% | 94,02% | Linear |
| 2011 | 91,34% | 95,96% | 93,74% | 94,09% | 97,57% | Linear |
| 2012 | 99,03% | 95,46% | 98,79% | 98,48% | 98,99% | Linear |
| 2013 | 98,65% | 96,96% | 99,69% | 99,75% | 99,64% | Linear |
| 2014 | 97,05% | 97,36% | 97,23% | 99,75% | 98,94% | Linear |
| 2015 | 94,90% | 91,88% | 99,82% | 98,04% | 99,41% | Linear |
| 2016 | 98,24% | 85,59% | 97,10% | 96,59% | 96,66% | Linear |
| 2017 | 99,53% | 96,08% | 99,67% | 97,85% | 96,37% | Linear |
| 2018 | 99,35% | 96,84% | 99,01% | 98,45% | 99,15% | Linear |
| 2019 | 98,18% | 96,62% | 98,13% | 94,67% | 96,20% | Linear |
| 2020 | 88,16% | 67,88% | 83,84% | 90,39% | 84,60% | Linear |
| **Average** | **95,24%** | **92,56%** | **95,11%** | **95,79%** | **96,51%** | **100%** |

6.226 nodes were used for revenue, 4.609 for net income or loss, 6.457 for current assets, 6.193 for fixed assets, and 6.336 for equity in random forest models, each consisting of 1,000 decision trees.

The average success of the forecasts regarding the revenue amount of the business was calculated as 95.24%. The highest success in the forecasts for the Revenue amount was achieved in 2017 with 99.53%. The highest deviation in the forecast occurred in the forecasts for 2010. Forecasting success in 2010 remained at the level of 83.17%. The technique showed a forecasting success of over 90% in 9 of 11 years and between 80% and 90% in two years.

The average success rate of the forecasts regarding the profit or loss amounts was calculated as 92.56%. While the lowest forecasting success was shown in 2020 with 67.88%, the highest forecasting success was achieved in 2010 with 97.53%. However, the forecast of the gain or loss direction of the business in all years was made correctly, and 100% success was achieved in this forecast.

When the estimated amounts for the current assets item were compared with the actual amounts, the average forecast success of the technique was calculated as 95.11%. While the highest forecast success was realised in 2015 amounts, the highest deviation was in 2010, with 79.16% forecast success. The deviation in 2010 is thought to be due to the small amount of uploaded train data. The model, which showed a success of over 90% in 9 of the forecasts made for 11 years, achieved a forecasting success of 83.84% in the last year.

While the total fixed assets of the enterprise were estimated to be 99.75% successful in 2013 and 2014, this rate remained at 85.65% in 2010. The overall forecasting success was calculated as 95.97%.

The forecasting success of the technique for the Equity item reached its highest level in 2013 with 99.64%. The year with the highest deviation in forecasts is 2020, with a forecasting success of 84.60%.

**Table 3.** Success Rates of Lokman Hekim Financial Forecast

| Year | Revenue | Net Income/Loss | Current Assets | Fixed Assets | Equity | Gain/Loss Direction |
|---|---|---|---|---|---|---|
| 2010 | 74,04% | 13,10% | 73,74% | 80,47% | 67,53% | Linear |
| 2011 | 76,31% | 98,24% | 78,38% | 88,22% | 95,14% | Linear |
| 2012 | 98,95% | 95,25% | 91,96% | 85,31% | 92,31% | Linear |
| 2013 | 95,41% | 98,28% | 97,30% | 92,59% | 97,13% | Linear |
| 2014 | 96,64% | 85,75% | 97,17% | 98,09% | 98,55% | Linear |
| 2015 | 89,70% | 93,82% | 97,74% | 96,55% | 92,56% | Linear |
| 2016 | 94,85% | 88,42% | 81,42% | 81,18% | 99,58% | Linear |
| 2017 | 96,88% | 99,28% | 99,81% | 98,65% | 99,03% | Linear |
| 2018 | 99,19% | 97,37% | 98,15% | 97,99% | 98,32% | Linear |
| 2019 | 95,38% | 90,89% | 93,79% | 95,24% | 97,71% | Linear |
| 2020 | 97,30% | 95,22% | 99,40% | 90,89% | 85,18% | Linear |
| **Average** | **92,24%** | **86,87%** | **91,71%** | **91,38%** | **93,00%** | **100%** |

6.182 for revenue, 5.511 for net income or loss, 6.468 for current assets, 5.379 for fixed assets, and 6.105 nodes for equity were used in random forest models, each consisting of 1,000 decision trees.

The average success of the forecasts regarding the revenue amount of the business was calculated as 92.24%. The highest success in the forecasts for the Revenue amount was achieved in 2018 with 99.19%. The highest deviation in the forecasts occurred in the forecasts for 2010. The forecast success in 2010 remained at the level of 74.04%. The low forecasting success in 2010 is thought to be due to the scarcity of train data. The technique showed over 90% forecasting success in 8 of 11 years.

It has been seen that the business made a loss in 2013 and a profit in other years. The average success rate of the forecasts regarding gain or loss amounts was 86.87%. While the lowest forecasting success was shown in 2010 with 13.10%, the highest forecasting success was achieved in 2017 with 99.28%.

When the estimated amounts for the current assets item were compared with the actual amounts, the average forecasting success of the technique was calculated as 91.71%. While the highest forecasting success was realised in 2017, with 99.81%, the highest deviation was in 2010, with a forecasting success of 73.74%.

While the total fixed assets of the enterprise were estimated to be 98.65% successful in 2017, this rate remained at 80.47% in 2010. The overall forecasting success was calculated as 91.38%. Although the technique forecasted an increase in fixed assets in 2016, the increase in fixed assets was more than expected.

In the forecasts made for Equity, the technique's success reached the highest level in 2016 with 99.58%. The highest deviation in the forecasts was in 2010, with a forecasting success of 67.53%.

**Table 4.** Success Rates of Mepet Financial Forecast

| Year | Revenue | Net Income/Loss | Current Assets | Fixed Assets | Equity | Gain/Loss Direction |
|---|---|---|---|---|---|---|
| 2010 | 88,47% | 90,50% | 73,55% | 96,12% | 96,01% | Linear |
| 2011 | 94,73% | 97,57% | 99,89% | 76,00% | 94,38% | Linear |
| 2012 | 99,77% | 92,45% | 98,85% | 81,21% | 94,69% | Linear |
| 2013 | 99,18% | 93,61% | 94,49% | 91,40% | 92,76% | Linear |
| 2014 | 96,58% | 94,26% | 97,90% | 99,66% | 99,85% | Linear |
| 2015 | 96,29% | 87,07% | 97,33% | 96,97% | 97,70% | Linear |
| 2016 | 97,52% | 87,87% | 79,47% | 84,84% | 99,18% | Linear |
| 2017 | 95,19% | 89,25% | 97,72% | 96,85% | 99,75% | Linear |
| 2018 | 98,93% | 88,95% | 96,29% | 96,67% | 98,59% | Linear |
| 2019 | 91,75% | 90,97% | 90,00% | 96,77% | 96,55% | Linear |
| 2020 | 93,09% | 87,03% | 92,35% | 95,85% | 98,60% | Linear |
| **Average** | **95,59%** | **90,87%** | **92,53%** | **92,03%** | **97,10%** | **100%** |

5,742 nodes for revenue, 6,588 for net income or loss, 6,412 for current assets, 5,868 for fixed assets, and 6,825 for equity were used in random forest models, each of which consists of 1,000 decision trees.

The highest success in estimating the Revenue amount was achieved in 2012 with 99.77%. The highest deviation in the forecasts occurred in the estimates for 2010. Forecasting success in 2010 remained at the level of 88.47%.

The average success rate of the forecasts regarding gain or loss amounts was 90.87%. While the lowest forecasting success was shown in 2020 with 87.03%, the highest forecasting success was achieved in 2011 with 97.57%. However, the forecast of the profit or loss direction of the enterprise in all years was made correctly, and 100% success was achieved in this forecast.

When the estimated amounts for the current assets item were compared with the actual amounts, the average forecasting success of the technique was calculated as 92.53%. While the highest forecasting success was realised in 2011, with 99.89%, the highest deviation was in 2010, with a forecasting success of 73.55%.

For the fixed assets item, it has been seen that the highest forecast success of the technique was in 2014, and the lowest was in 2011. While the total fixed assets of the enterprise were estimated to be 99.66% successful in 2014, this rate remained at 76% in 2011. The overall forecasting success was calculated as 92.03%. While forecasts were made in 8 of the 11 years, a success rate of over 90% was observed, and a success rate between 70% and 80% was observed in two years.

The forecast success of the technique in Equity item reached its highest level in 2014 with 99.85%. The year with the highest forecast deviation was 2013, with a forecasting success of 92.76%. The fact that the changes in equity could be estimated to a large extent in all years stands out as a positive indicator from a technical point of view. In all of the forecasts made for 11 years, over 90% of forecast success has been observed. The average success of the estimates made regarding equity was calculated as 97.10%.

**Table 5.** Success Rates of Migros Financial Forecast

| Year | Revenue | Net Income/Loss | Current Assets | Fixed Assets | Equity | Gain/Loss Direction |
|---|---|---|---|---|---|---|
| 2010 | 80,66% | 74,27% | 92,93% | 98,19% | 89,30% | Linear |
| 2011 | 89,57% | 86,61% | 95,56% | 96,84% | 89,59% | Linear |
| 2012 | 96,41% | 99,68% | 99,90% | 97,85% | 91,41% | Linear |
| 2013 | 84,77% | 79,97% | 97,54% | 96,56% | 98,44% | Linear |
| 2014 | 94,96% | 83,18% | 94,89% | 99,24% | 93,65% | Linear |
| 2015 | 98,24% | 88,78% | 94,10% | 94,40% | 72,06% | Linear |
| 2016 | 90,80% | 94,47% | 97,38% | 97,28% | 68,90% | Linear |
| 2017 | 98,72% | 95,07% | 97,80% | 94,85% | 85,65% | Linear |
| 2018 | 99,02% | 92,76% | 99,26% | 98,89% | 97,29% | Linear |
| 2019 | 94,65% | 96,44% | 97,56% | 92,12% | 89,92% | Linear |
| 2020 | 81,68% | 99,22% | 86,16% | 96,62% | 17,27% | Linear |
| **Average** | **91,77%** | **90,04%** | **95,73%** | **96,62%** | **81,23%** | **100%** |

7,631 nodes for revenue, 6,937 nodes for net income or loss, 5,954 for current assets, 3,991 for fixed assets, and 7,644 nodes for equity were used in random forest models, each of which consists of 1,000 decision trees.

The average success of the forecasts regarding the revenue amount of the business was calculated as 91.77%. The highest success in estimating the revenue amount was achieved in 2018, with 99.02%. The highest deviation in the estimates occurred in the forecasts for 2010. Forecasting success in 2010 remained at the level of 80.66%. The technique showed a forecasting success of over 90% in 7 of 11 years and between 80% and 90% in 4 years.

The average success of the forecasts regarding the net income or loss amounts was calculated as 90.04%. While the lowest forecasting success was observed in 2010, with 74.27%, the highest forecasting success was achieved in 2012, with 99.68%. However, the forecast of the gain or loss direction of the business in all years was made correctly, and 100% success was achieved in this forecast.

When the estimated amounts for the current assets item were compared with the actual amounts, the average forecasting success of the technique was calculated as 95.73%. While the highest forecasting success was 99.90% in 2012 amounts, the highest deviation was in 2020 amounts with 86.16% forecasting success.

While the total fixed assets of the business were estimated to be 99.24% successful in 2014, this rate remained at 92.12% in 2019. The overall forecasting success was calculated as 96.62%. Over 90% of forecast success was observed in all 11 years.

The forecast success of the technique in equity item reached the highest level in 2013 with 98.44%. The year with the highest forecast deviation was 2020, with a forecasting success of 17.27%. Although the decrease in equity was estimated in the model in 2020, the excessive size of the decrease caused a deviation in the forecast. The fact that the changes in equities between 2010 and 2019 could be estimated to a large extent stands out as a positive indicator from a technical point of view. While a forecasting success of over 90% was observed in 4 of the 11 years, a success rate of between 80% and 90% was observed in 4 years.

**Table 6.** Average Forecast Success by Item and Year

| Year | Revenue | Net Income/Loss | Current Assets | Fixed Assets | Equity | Average |
|---|---|---|---|---|---|---|
| 2010 | 83,63% | 66,53% | 81,85% | 88,10% | 85,00% | 81,02% |
| 2011 | 88,87% | 91,14% | 90,72% | 86,25% | 92,81% | 89,96% |
| 2012 | 95,38% | 95,51% | 96,23% | 84,59% | 90,84% | 92,51% |
| 2013 | 95,41% | 88,93% | 91,80% | 89,17% | 91,99% | 91,46% |
| 2014 | 95,57% | 87,12% | 96,00% | 92,71% | 93,85% | 93,05% |
| 2015 | 94,09% | 88,38% | 95,55% | 88,78% | 88,71% | 91,10% |
| 2016 | 89,82% | 85,98% | 82,18% | 89,27% | 91,65% | 87,78% |
| 2017 | 97,41% | 91,11% | 96,52% | 96,59% | 96,07% | 95,54% |
| 2018 | 99,30% | 93,60% | 98,34% | 98,21% | 97,99% | 97,49% |
| 2019 | 95,50% | 93,38% | 93,35% | 95,12% | 92,93% | 94,06% |
| 2020 | 88,43% | 88,91% | 80,77% | 94,63% | 76,78% | 85,90% |
| **Average** | **93,04%** | **88,24%** | **91,21%** | **91,22%** | **90,78%** | **90,90%** |

The overall success of the forecast of the revenue item was calculated as 93.04%. Revenue was estimated to be more than 90% successful in 7 of 11 years and between 80% and 90% in other years.

The overall success of the forecast regarding the net income or loss item was calculated as 88.24%. It has been seen that the forecasts regarding the net income or loss item were successful at over 90% in 5 of 11 years.

The overall success of the forecast of the sum of current assets was calculated as 91.21%. Forecasts for the total of current assets are successful more than 90% in 8 of 11 years.

The overall success of the forecast of the total fixed assets was calculated as 91.22%. The total fixed assets were estimated to be between 80% and 90% successful in 6 of 11 years and over 90% in 5 of them. It has been known that increases and decreases in fixed assets can be affected by many decisions, such as purchasing new assets, renewal, revaluation, or the applied depreciation method. In this respect, it has been thought that the overall forecasting success of 91.36% was positive.

In 2010 and 2011, forecast success was calculated low due to insufficient training data. The reason for the deviations in 2016 is thought to be the political events in Turkey in the same year. However, it is thought that the reason for the decrease in forecasting success in 2020 is the Covid-19 pandemic.

The overall success of the forecast of the sum of equities was calculated as 90.78%. It has been seen that the forecasts regarding the sum of equities are successful at more than 90% n 8 of 11 years. As with other forecasts, the deviations in the estimates for the total equity have been thought to be due to insufficient train data in 2010 and non-financial factors in 2016 and 2020.

When the overall forecasting success is analysed by years, the deviation caused by the scarcity of train data in 2010 can be seen. In addition, deviations arising from the effects of non-financial factors in 2016 and 2020 have also come to the table. Because it has been known that cyclical factors in 2016 and the Covid-19 Pandemic in 2020 affected businesses both in macro and micro terms. In the forecast of the net income item, it has been forecasted that the forecast success can reach higher levels by including variables such as changes in energy prices, the stock cost flow assumption applied, depreciation policy, and tax-exempt incomes, apart from the variables used in the analysis. Considering that it is aimed to estimate the amounts, it has been thought that the forecast success of 90.90% is high enough.

## 6. CONCLUSION AND FINDINGS

In this study, the financial statements of five businesses operating in different sectors and whose shares were traded in Borsa Istanbul between the years 2009-2020, the inflation rate, US Dollar exchange rate, unemployment rate, minimum wage increase rate, Gross Domestic Product growth rate and CBT Interest Rate were used as the data set. The data specified in question was analysed with the random forest technique, which is a machine learning technique, and financial statement items between 2010-2020 were estimated.

For each estimated financial statement item, the financial data of all previous years are used as train data. The businesses selected for the research are as follows:

- Afyon Çimento Inc.
- Arçelik Inc.
- Lokman Hekim Inc.
- Mepet Inc.
- Migros Inc.

The estimated financial statement items of the businesses above are as follows:

- Revenue,
- Net income or loss,
- Total current assets,
- Total Fixed assets and
- Equity.

When all the forecasts are examined in general, it has been determined that the overall success of the technique is high and it can be used effectively in the financial forecast. When the deviations in the forecasts are analysed, it has been seen that the forecasts made with only one-year data are 81.02% on average, the forecasts made with the two-year data are 89.96%, and the forecasts made with the three-year data are 92.51% successful. The overall forecast success of the technique was calculated as 90.90%. It has been thought that forecast should be made with at least two years of train data to obtain healthy and reliable results. Considering the analysis and comparisons, it has been concluded that the random forest technique can be used effectively in financial forecasting.

The effect of non-financial variables on forecasts was also revealed in the analyses. In future studies, it will be possible to conduct studies that include macroeconomic and non-financial factors. It has been known that the butterfly effect is felt in the global market. For example, due to the decrease in microchip production in the People's Republic of China with the Covid-19 Pandemic, the automotive, white goods, and almost all electronics markets were adversely affected. For this reason, it has been thought that including non-financial factors in the financial forecast is expected to significantly increase the success of the forecasts.

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