T.C.
İSTANBUL KÜLTÜR UNIVERSITY
INSTITUTE OF GRADUATE STUDIES

THE IMPACT OF COVID-19 ON THE TECHNOLOGY SECTOR: THE CASE OF TURKISH CONSULTANCY COMPANY

MASTER OF SCIENCE THESIS

Eda GÖZÜTOK
2000005521

Department: Industrial Engineering
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June 2022 Eda GÖZÜTOK

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LIST OF SYMBOLS

R^2	Coefficient of Determination
KNIME	Konstanz Information Miner
WHO	World Health Organization
OECD	Organization for Economic Co-operation and Development
GDP	Gross Domestic Product
Q1	Quarter 1
Q2	Quarter 2
Q3	Quarter 3
Q4	Quarter 4
ML	Machine Learning
GBR	Gradient Boosting Regression
LR	Linear Regression
RFR	Random Forest Regression
IMF	International Monetary Fund
TUIK	Turkish Statistical Institute
IT	Information Technology
ICT	Information and Communication Technologies
NIST	National Institute of Standards and Technologies
TCS	TATA Consultancy Services
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error
MSE	Mean Squared Error
MSD	Mean Signed Difference
MAPE	Mean Absolute Percentage Error

Üniversite	**: İstanbul Kültür Üniversitesi**
Enstitü	**: Lisansüstü Eğitim Enstitüsü**
Anabilim Dalı	**: Endüstri Mühendisliği**
Programı	**: Mühendislik Yönetimi**
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ÖZET

COVID-19'UN TEKNOLOJİ SEKTÖRÜNE ETKİSİ:

TÜRK DANIŞMANLIK ŞİRKETİ ÖRNEĞİ

Eda GÖZÜTOK

COVID-19 Çin'in Wuhan şehrinde ortaya çıktığından beri hem ekonomik hem de sosyolojik olarak tüm dünyayı etkilemiştir. Olumlu veya olumsuz etkilerini anlamak için farklı analiz çalışmaları ve anketler yapılarak birçok çalışma yayınlanmıştır. Ülke ve sektörel olarak farklı etkiler görülmektedir. Bu çalışmada teknoloji alanında hizmet veren bir danışmanlık şirketi üzerinde COVID-19'un etkileri araştırılmıştır. Şirketin COVID-19 öncesine ait beş yıllık satış verisi kullanılarak KNIME üzerinden makine öğrenmesi ile COVID-19 dönemine ait satış verileri tahmin edilmiştir. Tahminler lineer, gradient boosting ve random forest olmak üzere üç farklı regresyon modeli kullanılarak yapılmıştır. Her model hesaplanan belirleme katsayısı (R^2) üzerinden karşılaştırılarak en iyi model seçilmiştir. Seçilen bu model ile COVID-19'un şirket üzerindeki etkisi yorumlanmıştır.

Anahtar Kelimeler: COVID-19, regresyon modelleri, tahminleme, KNIME, makine öğrenmesi.

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ABSTRACT

THE IMPACT OF COVID-19 ON THE TECHNOLOGY SECTOR:

THE CASE OF TURKISH CONSULTANCY COMPANY

Eda GÖZÜTOK

Since COVID-19 emerged in Wuhan, China, it has affected the whole world both economically and sociologically. Many studies have been published by making different analysis studies and surveys to understand their positive or negative effects. It seemed different effects in terms of country and sector. In this study, the effects of COVID-19 on a consulting company serving in the field of technology were investigated. Using the company's five-year sales data from the pre-COVID-19 period, sales data for the COVID-19 period were predicted by machine learning over KNIME. Predictions were made using three different regression models: linear, gradient boosting, and random forest. Each model was compared over the calculated coefficient of determination (R^2) and the best model was selected. With this chosen model, the impact of COVID-19 on the company has been interpreted.

Keywords: COVID-19, pandemic, regression models, KNIME, forecasting, prediction.

Science Code: ….

1. INTRODUCTION

The coronavirus pandemic, also known as the COVID-19 pandemic affects the world socially, physiologically, and also economically. Several papers, studies, and, articles were published to explain those effects with different analyses from different angles. According to World Health Organization (WHO), more than 520 million people were affected by COVID-19 .and also more than 6 million people passed away until May 2022 (WHO, 2022)

1.1. Research Background

COVID-19 was first shown up in Wuhan, Hubei Province on 31st December 2019. COVID-19 was confirmed as a pandemic on 2020, March 11 by World Health Organization. Before the declaration as a pandemic, it spread to 18 countries from China (WHO, 2022).

The first case of Turkey's COVID-19 was discovered on March 11, 2020. More than 5 million people were infected after the first incidence, and nearly 100,000 people died until the beginning of May (*T.C. Sağlık Bakanlığı*, 2022).

Out of 193 countries' economics, 167 economies saw a negative rate in 2020. Almost 79% of the world economy accounted for by these 167 economies. China was the worst affected country in the first quarter of 2020 with an economic decrease of 9,7%. Iceland and France followed China on the list. India, United Kingdom, and Spain were the most damaged countries during the second quarter of 2020 and the world economy shrunk 32,9 percentages. In the third quarter of 2020, 33,1% growth came amid a resurgence in consumer activity. In the last quarter of 2020, the economy maintained growing by 4% even with a slight rate compared to the third quarter. Total growth in 2020 was 3,6% and only two countries which are China and Turkey saw a positive economic rate at end of the 2020 (Organisation for Economic Co-operation and Development, 2021).

According to data from the Presidency of Strategy and Budget, during the COVID-19 pandemic, Turkey's economy grew by 1,8 percent compared to last year. The first, third, and fourth quarters of Gross Domestic Product (GDP) increased by 4,5%, 6,3%, and 5,9% respectively in 2020. However, in the second quarter of 2020 GDP decreased 10,3% in comparison to last year. Table 1.1 indicates sectoral growth rate changes from 2019 to 2020.

Table 1.1 GDP sectoral growth rates in 2019-2020

Sectors	2019					2020				
	Q1	Q2	Q3	Q4	Yearly	Q1	Q2	Q3	Q4	Yearly
Agriculture	3,9	4,6	4,0	2,5	3,7	1,8	3,7	6,0	4,0	4,8
Industry	-5,2	-4,0	1,0	4,3	-1,0	6,3	-16,5	7,3	10,3	2,0
Production Industry	-6,7	-5,7	-0,5	3,6	-2,3	7,1	-18,3	8,6	10,5	2,1
Construction	-8,2	-11,7	-9,0	-5,2	-8,6	-2,8	-3,9	4,7	-12,5	-3,5
Services	-1,1	-1,0	0,3	7,0	1,4	3,2	-10,8	4,4	3,3	0,0
Expert of Goods and Services	9,1	6,2	4,7	0,6	4,9	-1,8	-36,9	-22,1	0,0	-15,4
Import of Goods and Services	-29,6	-18,6	3,6	27,8	-5,3	21,4	-7,7	16,4	2,5	7,4
Gross Domestic Product (GDP)	**-2,6**	**1,7**	**1,0**	**6,4**	**0,9**	**4,5**	**-10,3**	**6,3**	**5,9**	**1,8**

Note. Adapted from https://www.sbb.gov.tr/butce-genel-faaliyet-raporlari/. Copyright 2020 Presidency of Strategy and Budget, 2021.

COVID-19 appeared suddenly and changed the expectations of companies. Forecasting is substantial to plan production, efficiently allocate resources and workforces, marketing strategies for companies. Machine learning (ML) is the study of computer algorithms that can learn and develop on their own through experience and data (Mitchell T.,1997). Forecasting is one of the applications of machine learning.

This research concentrated to analyze the impacts of COVID-19 in the case of a Turkish consultancy company in technology sector. With seven years of sales data collected made forecasting using different regression model from the Konstanz Information Miner (KNIME) platform. The regression models are gradient boosting regression (GBR), linear regression (LR) and random forest regression (RFR).

1.2. Research Questions/Hyphothesis

This study will answer the following questions.

- How has the world been affected economically by COVID-19?
- How machine learning can be applied to sales data?
- What is the impact of COVID-19 in this study case?

1.3. Aim of The Research

The aim of this study is to understand the impact of COVID -19 on a Turkish consulting firm in the technology sector. The sales data for previous years are separated into eight categories. Three categories that have major sales amounts were used for this study. And these three main categories are divided into 12 subcategories. Six sectors were grouped as others and seven sectors were used for forecasting. Each year is divided into four quarters.

Forecasting was made with a machine learning tool named KNIME for three different models. Every model was implemented in two eras. One of them is before COVID-19 and the other one after COVID-19. We're trying to figure out how COVID-19 was affect sales in this study case.

1.4. Research Significance /Contribution

After COVID-19 appeared, more than 50.000 papers were published on the Science Direct website. Pandemic affected various sectors like tourism, accommodation, education, aviation, production, automotive, and food. More than one-fifth of papers are related to the economic effect of COVID-19 from different angles (ScienceDirect, 2020). While Vall Castelló and Lopez Casasnovas (2020) examined sales of supermarkets in Spain, Lu and friends (2021) examined Beijing (Lu et al., 2021; Vall Castelló & Lopez Casasnovas, 2021). Even if the study of Fu and Shen (2020) shows adverse effects of COVID-19 in the energy industry, research of Hayakawa and Mukunoki (2021) shows affirmative effects of COVID-19 in the medical products industry (Fu & Shen, 2020; Hayakawa & Mukunoki, 2021; Vall Castelló & Lopez

Casasnovas, 2021). This study will be a research that will focus on analyzing the impacts of COVID-19 on the technology sector in a Turkish company.

1.5. Scope and Structure of Thesis

This thesis comprises six chapters. Chapter 1 contains general information about COVID-19 and its economic impacts. Chapter 2, there is a review of previous studies published which provides a summary of similar studies about the economic impacts of COVID-19 in different sectors around the world. Machine learning, forecasting methodologies, and the KNIME tool which is used for modeling information are given in Chapter 3. In Chapter 4, preparing sales data, and forecasting methods are explained step-by-step. Numerical results and comments are given in Chapter 5. Finally, Chapter 6 highlighted and presented results and findings in this case.

2. LITERATURE REVIEW

After the first case of COVID-19 in China, it spread very quickly around the world. Countries take cautions like curfews, forbidden flights, and stopping production to minimize the spread of COVID-19. This section provides information about the COVID-19 pandemic, examples of economic effects around the world, and economic views on Turkey.

2.1. COVID-19 Pandemic Around World

COVID-19 became the largest pandemic in the last centuries. From the earliest cases to the beginning of March 2022, 456.781.285 cases and 6.062.188 deaths were confirmed (WHO,2022). Figure 2.1 shows total cases, figure 2.2 shows daily cases and figure 2.3 is about total death until March 2022. According to cases that are recorded, 221 countries are affected by COVID-19 and this number also includes islands (Worldometers, n.d.-a).

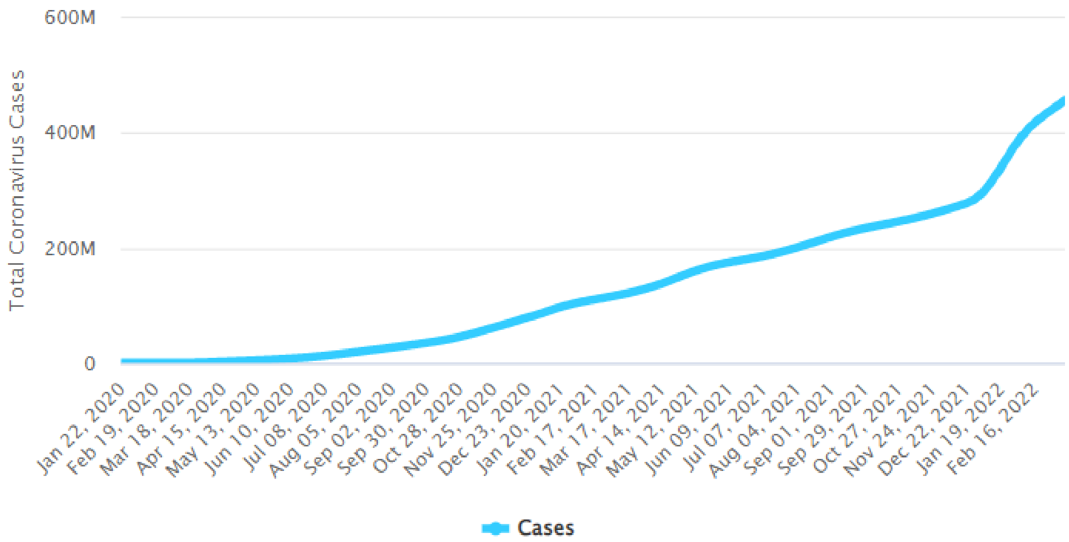

Figure 2.1 COVID-19 total cases on world

Note. Total COVID-19 cases. From Worldometers, *COVID Live – Coronavirus Statistics –* by Worldometers, n.d. (https://www.worldometers.info/coronavirus/)

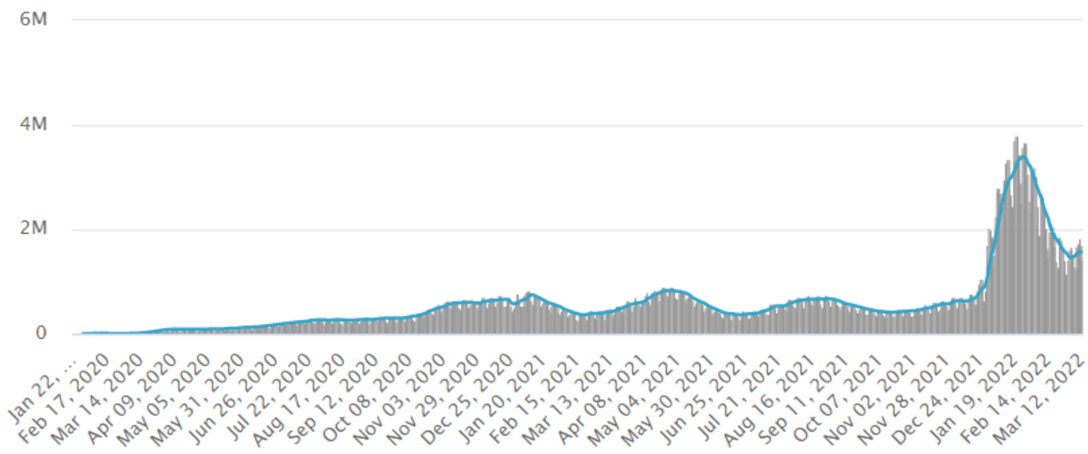

Figure 2.2 COVID-19 daily cases on world

Note. Daily COVID-19 cases. From Worldometers, *COVID Live - Coronavirus Statistics –* by Worldometers, n.d. (https://www.worldometers.info/coronavirus/)

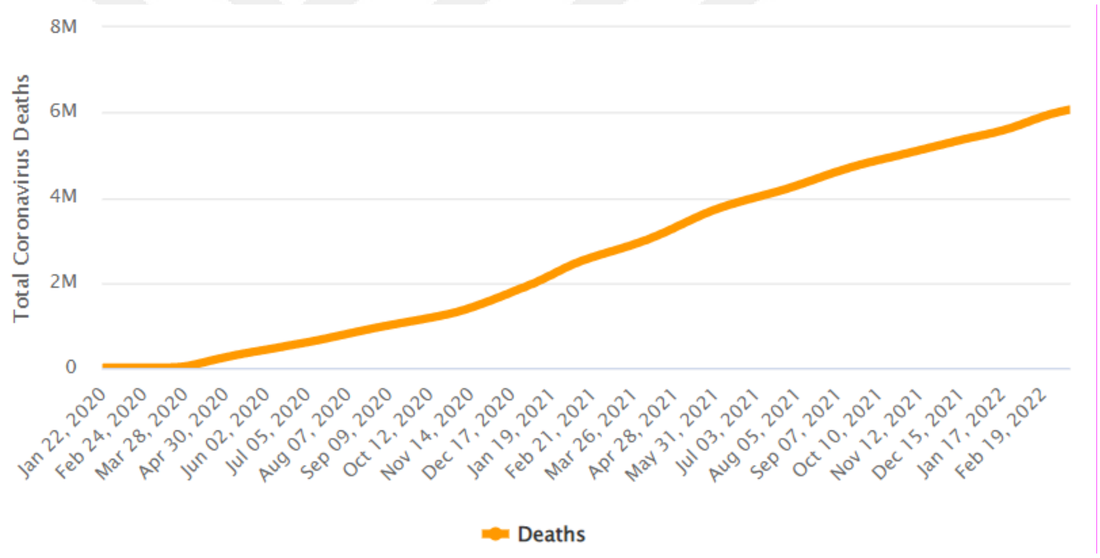

Figure 2.3 COVID-19 total deaths on world

Note. Total COVID-19 deaths. From Worldometers, *COVID Live - Coronavirus Statistics –* by Worldometers, n.d. (https://www.worldometers.info/coronavirus/)

Every country takes precautions to slow down the spread of COVID-19 such as physical or social distancing, quarantining, ventilation of indoor spaces, and restriction to travel. Megatsari et al. studied the psychological impacts of pandemics in Indonesia. Their study shows some age groups have high anxiety (Megatsari et al., 2020). According to a survey that examines the impact of COVID-19 on psychiatric patients, patients have more psychiatric symptoms during lockdown (Hao et al., 2020).

2.2. COVID-19 Economic Effects on World

According to Organization for Economic Co-operation and Development (OECD), countries' economies affected adversely in the beginning of the pandemic. Recovery started however lower-income economies still needs time. Several studies have been published showing the impact of COVID-19 (Organisation for Economic Co-operation and Development, 2021).

According to a survey among farm owners and workers, in households in the Caribbean, COVID-19 affected strongly the agricultural system such as a decrease in revenue, production decreasing because of distance problems in marketing, and managing problems due to lack of labor. This study shows the adaptation of farmers to this situation improves the links between farmers and society (Blazy et al., 2021).

Spain is one of the worst affected countries during the COVID-19 pandemic. Vall Castelló and Lopez Casasnovas (2020) examine the COVID-19 effects on the sales of a supermarket chain for 12 various food and three age groups in Spain. Their study shows, that there is strong stockpiling especially in the first week of lockdown, with fear of being infected was decreased sales rates and they could not find any effect in the aged 66 and over group analysis (Vall Castelló & Lopez Casasnovas, 2021).

According analysis in China about COVID-19's impacts on the demand and the supply side of the electric vehicle industry, shows a negative effect on sales in the short term. However, preferring local suppliers because of importing products and changing traditional marketing channels as a consequence of social distancing will be a beneficial impact in the long term (Wen et al., 2021).

Wieczorek-Kosmala (2021), analyzes the risk preparedness of the hospitality business industry according to their financial slack holdings during COVID-19. As a consequence of this analysis, they examine evaluate holdings and persistence of financial slack resources and propose an effective system to improve the situation (Wieczorek-Kosmala, 2021).

Hayakawa and Mukunoki (2021) investigate international trade changes during the first six months of 2019 and 2020. The report includes exports from 34 countries to 173 countries. There are negative effects on leather, mineral, and footwear products, and transport kits especially in the fourth and fifth months of 2020 whereas there are effects positively in industries manufacturing medical products (Hayakawa & Mukunoki, 2021).

Maneenop and Kotcharin (2020) researched the effects on the airline stock prices of 52 airlines around the world during three different events during COVID-19. Event 1st is the first case in Thailand (January 13, 2020) which is the first infected country after China. Event 2nd is the lockdown in Italy (February 21, 2020). Event 3rd is the proclamation of COVID-19 as a global pandemic by WHO (March 11, 2020). They find overreaction to Event 3. Australia, Canada, the United Kingdom, and United State showed the worst reaction to Event 3 (Maneenop & Kotcharin, 2020).

Oil-dependent countries have two problems during COVID-19. One of them is the pandemic and the other one is the oil price collapse. According to research, IMF World Economic Outlook's GDP growth at the beginning and end of the outbreak in oil-dependent countries affected worse than expected forecast (Azomahou et al., 2021).

Fu and Shen (2020) study the effects in the energy industry of COVID-19 on corporate development using modeling analysis and tests. COVID-19 damaged the productivity of energy companies, and companies could not effort their fixed costs and expenses, as a result, an important damaging effect was found on the development of energy companies (Fu & Shen, 2020).

Menhat et al. (2021) investigate COVID-19 impacts on marine sectors, particularly shipping, fisheries, marine tourism, and the energy sector from January 2020 to June 2020. Study shows marine tourism was the most affected sector in Malaysia because the government considered as a non-essential sector. Shipping was affected lightly compared to other sectors (Menhat et al., 2021).

According to a study in China, electric energy, heating, mining, and environmental industry have been impacted negatively during the COVID-19. Even so, some industries show strong immunity for instance production, information technology, education, and healthcare (He et al., 2020).

Wang et al. (2020) studied the effects of COVID-19 in China on the insurance sector. They employ monthly regional panel sales data and stable effects models in their study. Study shows, that there are negative effects on property and personal insurance, and personal insurance was damaged more than that property insurance from the angle of insurance density and depth (Wang et al., 2020).

2.3. COVID-19 Pandemic in Turkey

The first case of COVID-19 appeared on 11th March 2020 in Turkey. After the first case, more than 5 million people were infected and almost 100.000 people died until the beginning of the May (*T.C. Sağlık Bakanlığı*, 2022) Figure 2.4 shows daily cases of Turkey (Worldometers, n.d.-b).

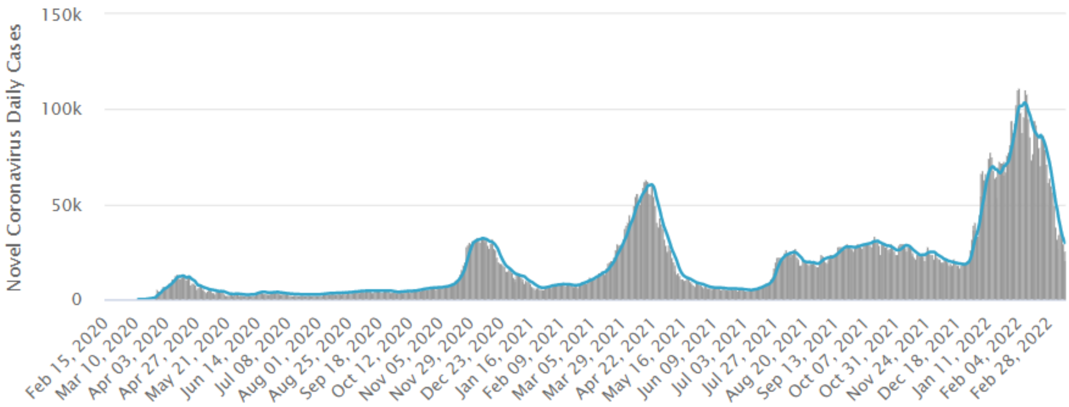

Figure 2.4 Daily cases of Turkey

Note. Daily COVID-19 cases in Turkey. From Worldometers, *COVID Live - Coronavirus Statistics* – by Worldometers, n.d. (https://www.worldometers.info/coronavirus/country/turkey)

Turkey Government took various precautions during this time. Important dates are;

- 1st February 2020- All the flights from China were stopped.
- 23rd February 2020- Iran border was closed and all flights to and from Iran were stopped.
- 29th February 2020- All flights to South Korea, Italy, and Iraqi were stopped (The Economist, 2020).
- 11th March 2020- First COVID-19 case was announced.
- 12th March 2020- Schools was closed from 16th March (Kandemir, 2020).
- 13th March 2020- All flights from several countries in Europe were suspended (Cantekin, 2020a).

- 16th March 2020- Indoor activities such as businesses and places of worship were halted (Cantekin, 2020b).
- 21st March 2020- A total curfew was announced for people who are elder 65 and who have immune system diseases such as asthmatics, cardiovascular problem, high blood pressure (Kandemir, 2020).
- 31st March 2020- The government announced an economic support program that will help small business not fire their workers (Ghosh, 2020a)
- 3rd April 2020- Total curfew was extended to people twenty and younger. During 15 days, in and out of Turkey's largest cities were prohibited (Ghosh, 2020b).
- 10th April 2020- A curfew was announced to everyone during weekends (Ghosh, 2020a).
- 23rd April 2020- More than 100.000 people infected from COVID-19 (*T.C. Sağlık Bakanlığı*, 2022)
- 4th May 2020- Return to normal life rules explained (*COVID-19 Pandemic in Turkey - Wikipedia*, n.d.).
- 5th May 2020- It has been reported that all main automotive factories will start operating again (*COVID-19 Pandemic in Turkey - Wikipedia*, n.d.).
- 1st June 2020- Public spaces were opened and domestic flights were resumed (The Economist, 2020).
- 2nd October 2020- Large meeting in public was prohibited until 1st December 2020 (Cantekin, 2020b).
- 26th November 2020- A new curfew was announced for people elder than 65 and younger than 20. Also, indoor activities such as businesses and places of worship were halted again (Overseas Security Advisory Council, 2020).
- 30th December 2020- The first Sinovac vaccine was brought to Turkey (*COVID-19 Pandemic in Turkey - Wikipedia*, n.d.).
- 13th January 2021- Emergency use approval was obtained for Sinovac vaccine and vaccination was initiated (*COVID-19 Pandemic in Turkey - Wikipedia*, n.d.).
- 3rd February 2021- The South African and Brazilian variant was also seen in Turkey (*COVID-19 Pandemic in Turkey - Wikipedia*, n.d.).

- 14th April 2021- A two-week partial closure was declared (*COVID-19 Pandemic in Turkey - Wikipedia*, n.d.).
- 26th April 2021- New full lockdown announced from 29th April to 17th May (The UN Refugee Agency, 2021)
- 17th May 2021- Partial closure was declared until 1st July (*COVID-19 Pandemic in Turkey - Wikipedia*, n.d.).
- 1st July 2021- The curfew was completely lifted (*COVID-19 Pandemic in Turkey - Wikipedia*, n.d.).
- 3rd May 2021- The obligation to wear masks in the open air has been removed (*COVID-19 Pandemic in Turkey - Wikipedia*, n.d.).

2.4. COVID-19 Economic Effects on Turkey

In compliance with data from the Presidency of Strategy and Budget, in the second quarter of 2020, most sectors were affected negatively by COVID-19 such as industry, construction, services, export, and import. During COVID-19 Turkey Government took provisions for decreasing the spreading speed of COVID-19 such as lockdowns, suspending air flights, and closing schools like other countries. The most affected sector in Turkey became exporting with a 15,4 percent decrease (T.C. Cumhurbaşkanlığı Strateji ve Bütçe Başkanlığı, 2022).

Exporting became a general problem in the world because of restrictions on air flights and curfews. During the pandemic, electronic microchip demand was increasing around the world. In Turkey, the automotive sector was affected negatively as a consequence of an interruption in production in the second quarter (Sabah, 2020).

Figure 2.5 shows the industrial production index from January to December. Even though there was a decrease in May, the end of the year index value was calculated at 144,7, and the average of the year value increased by 2,18% compared to last year (Türkiye Istatistik Kurumu, 2021)

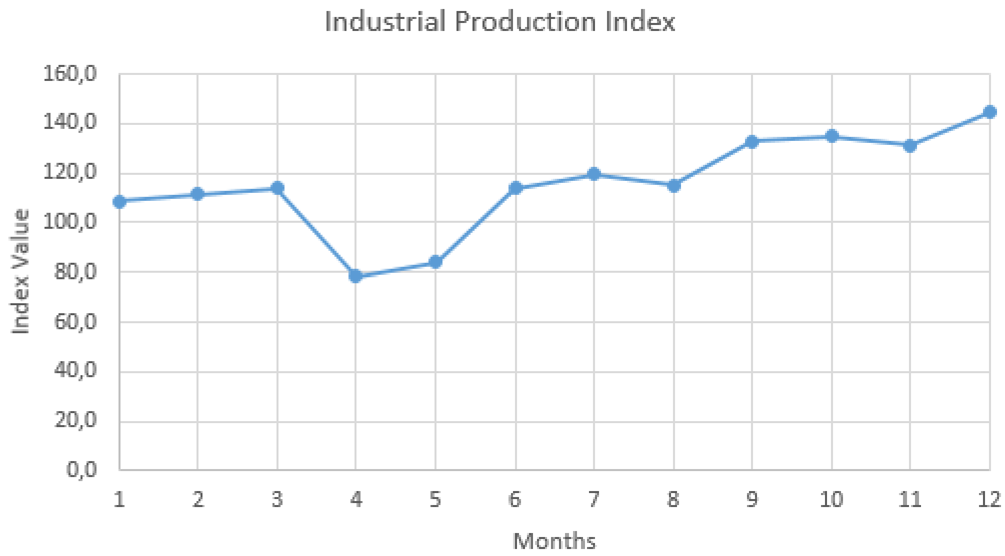

Figure 2.5 Industrial production index of Turkey in 2020

Figure 2.6 shows the production losses in 2020. Accommodation, tourism, construction, air transport, iron, and steel were affected adversely by more than 40 percent comprised of the previous year. Suspending air flights and lockdowns are the main reasons for this decrease.

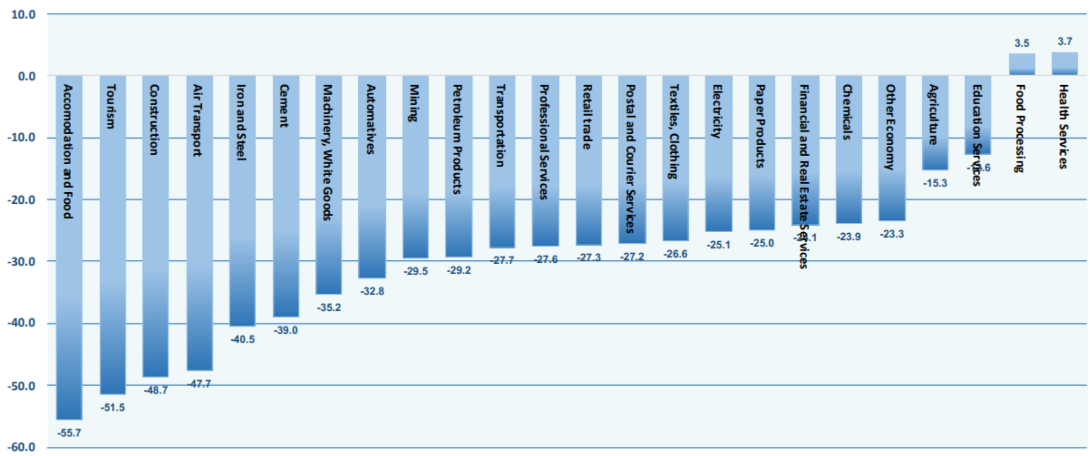

Figure 2.6 Real production losses (Against 2019 levels)

Note. Adapted from "A General Equilibrium Analysis of the Impact of the COVID-19 Outbreak on Turkey's Economy and a Policy Alternative to Protect Labor Incomes" by Voyvoda and Yeldan, 2020.

According to Turkish Statistical Institute (TUIK), the employment rate was 44% in January 2020. This rate decreased to 42,4 percent in half of the year 2020 and end of the year it was 42,8 percent. This rate includes agriculture, industry, services, and construction. The employment rate decreased 6,34% compared to 2019. Agricultural employment has declined the most among others (Türkiye Istatistik Kurumu, 2021).

2.5. COVID-19 Effects on Technology Consultancy Sector

The consultancy sector was affected adversely by COVID-19 in the first quarter of 2020. The consultancy sector continues to grow over the last 12 years. In 2019, the value of the sector reached $160 billion. Source Global Research gathered the opinions of hundreds of consulting organizations from around the world and concluded that the consultant sector could lose $30 billion in value by 2020. Figure 2.7 demonstrates the impacts of COVID-19 in a different region. The United States has a major percentage in the consultancy sector and according to the study, a 15% decrease is expected. Study shows Europe will be the worst affected by COVID-19 (Consultancy, 2020).

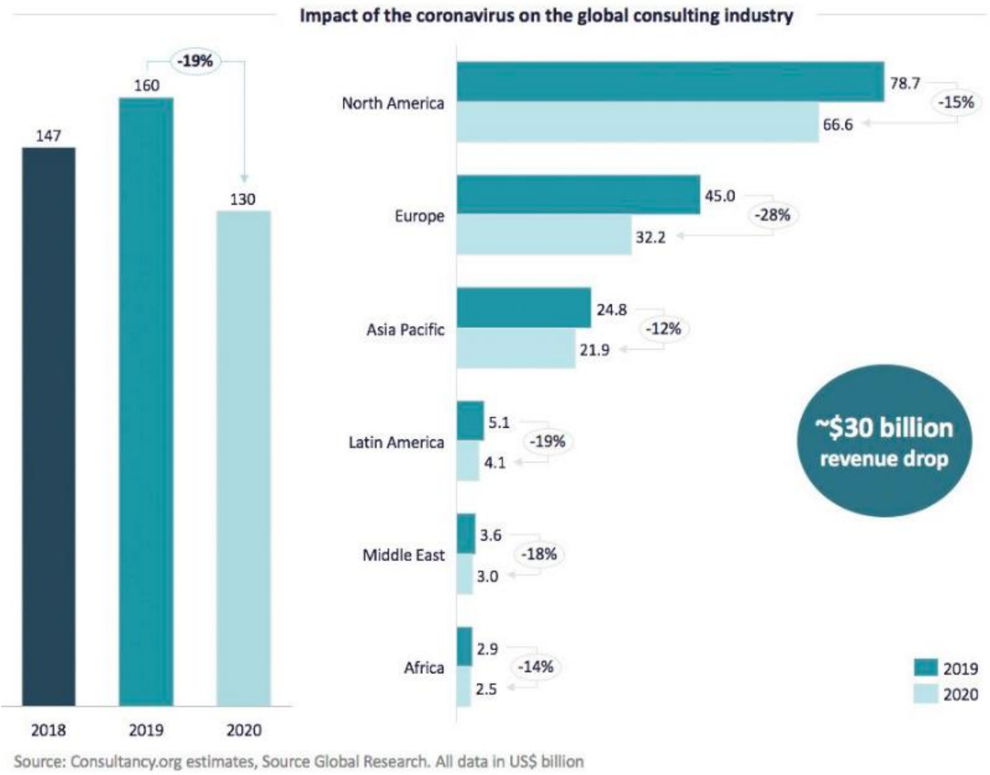

Figure 2.7 Impact of COVIS-19 in different region

Note. Adapted from *The impact of the Coronavirus on the global consulting industry*, by Consultancy, 2020 (https://www.consultancy.org/news/162/the-impact-of-the-coronavirus-on-the-global-consulting-industry)

According to the survey of Source Global Research, while business services, healthcare, energy and resources, manufacturing, and the public sector were in the higher risk group, financial services, pharma, retail and, technology and telecoms were in the lower-risk group (Consultancy, 2020).

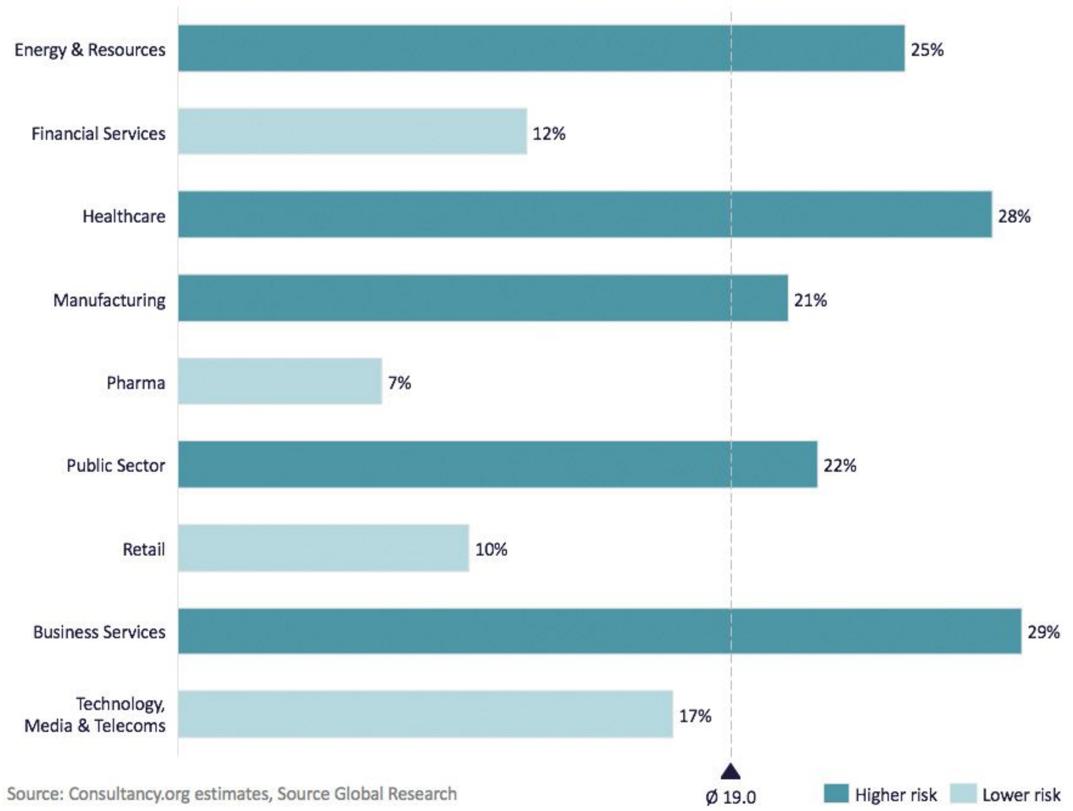

Figure 2.8 The impact of the COVID-19 on consulting by industry

Note. Adapted from *The impact of the Coronavirus on the global consulting industry*, by Consultancy, 2020 (https://www.consultancy.org/news/162/the-impact-of-the-coronavirus-on-the-global-consulting-industry).

Information technology (IT) consulting, often known as technology consulting, refers to services that assist clients in determining how to best employ information technology and digital to meet their business objectives. Remote working and curfews affected the demand for information and communication technologies (ICT) demands in a positive way (Taser et al., 2022). People need to do various things online such as shopping, working, studying and ICT makes them possible. That’s why companies investing in digitalization for adopting this period.

A survey about people’s grocery shopping choices shows there is a significant passing to online shopping during COVID-19. And it explains people who experienced online shopping are more likely to keep (Shen et al., 2022). Besides online shopping, the study by Mouratidis and Papagiannakis shows online learning, telework, telehealth, and teleconferencing also increased when compared to before COVID-19. While teleconferencing and e-learning increased by 34 percent, telework has a 31% increase (Mouratidis & Papagiannakis, 2021).

Microsoft Teams is a platform that combines teleconference, chat, and notes. Since it was released in November 2016, there was no significant growth like during the pandemic. Figure 2.9 shows the number of active daily users of Microsoft Teams. From March 2020 to April 2020, the number of users increased by 4,5 times. According to a survey of Microsoft Teams users in the United States, 29.71 percent of businesses used Microsoft Teams for remote work during the COVID-19 pandemic in 2020 (Statista, 2022).

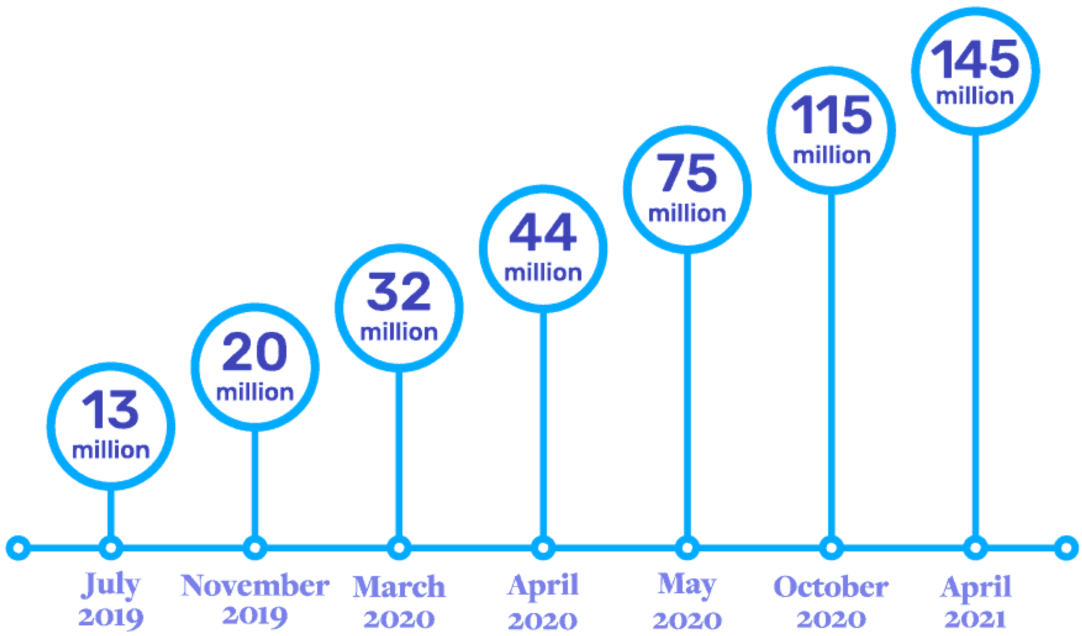

Figure 2.9 Number of teams active daily users

Note. Adapted from *Press Release & Webcast*, by Microsoft, 2021, (https://www.microsoft.com/en-us/Investor/earnings/FY-2021-Q1/press-release-webcast).

In addition to that, Zoom which is a teleconference platform like Microsoft Teams has more users with pandemics. While at end of the 2019, it has 10 million users, users number reached 30 million around the world in half of 2020. These platforms are using also between friends and families (Statista, 2022).

Acceptance of online teaching among nursing faculties was studied and the study shows nursing faculties have generally positive outcomes and they expected some concerns need to solve (Nurse-Clarke & Joseph, 2022).

Maharana and friends reviewed the literature for use of technology in Africa during COVID-19. 80 articles are categorized under clinical supplies and management .and disease surveillance and prevention. To minimize the spread of COVID-19, African countries deployed technology and new approaches to manage patients, monitor cases, and share information (Maharana et al., 2021). Also, Ahmad and friends suggest a convolutional neural network model diagnose COVID-19 by using multiple image processing techniques in their study (Ahmad et al., 2022).

During a pandemic, ICT generates solutions to understand the spread of COVID-19. For instance, the Australian Government released an application called CovidSafe to monitor and keep down the spreading of COVID-19 and invest $5 million for consulting, development, and maintenance (Consultancy, 2020). Also, Turkey Government launched a similar application named "Hayat Eve Sığar" to minimize spreading. The application generates a unique code and people use this code when they went to indoors such as in shopping malls, theaters, cafés and restaurants, and schools. 47 applications were used to contact tracing, Kassab and Graciano Neto examined the privacy of this application in their study (Kassab & Graciano Neto, 2021). Furthermore, according to a study, smartphones can be used to preserve continuity of care by avoiding physical contact and maintaining social distance as well as health care during a pandemic (Iyengar et al., 2020).

The National Institute of Standards and Technology (NIST) defines cloud computing as a model that provides ubiquitous, on-demand network access to a common pool of configurable computing resources (e.g., servers, networks, applications, storage, and services) that can be provisioned and released quickly with minimal management effort or service provider interaction (Mell & Grance, 2017).

According to a study, cloud computing is helping countries in the fight against COVID 19, economically and commercially in the education and health sectors (Alhomdy et al., 2021).

A study by Alhasan and Hasaneen shows the advantages of technologies used to fight against COVID-19. Contact tracing, natural language processing, machine learning for potential vaccinations, and modern imaging with artificial intelligence were used during this period (Alhasan & Hasaneen, 2021).

According to a survey of 263 senior UK banking executives, shows two-thirds are planning operational costs and want to invest in technology and automation. After COVID-19 they realized their potential agility and the necessity of digitalization (Appian, 2020).

For the acceptance and use of digital technology, Akinnuwesi and friends used a modified Unified Theory of Acceptance and Use of Technology model. They developed a new model for developing countries with multiple regression analysis (Akinnuwesi et al., 2022).

In compliance with a survey among agricultural companies in Pakistan, benefits of the blockchain technologies were identified in supply chains during COVID-19. It looks helpful for data management, easy transaction, an anti-fraud environment, a transparent supply chain and etc. (Khan et al., 2022).

Ntasis, Koronios, and Pappas (2021) investigate the impact of COVID-19 on the technology sector for TATA Consultancy Services (TCS). TATA Consultancy Services is a multinational information technology services and consulting company in India. They have 285 offices across 46 countries. They used the business and stock value performance of TCS for their study. According to a study, economic policy uncertainty has a negative effect on the stock price of TCS (Ntasis et al., 2021).

3. METHODOLOGY

This section explains general information about machine learning and implementation areas, three regression models that we used for prediction, and explains which data were collected and preprocessing of collected data.

3.1. Machine Learning

Machine learning (ML) is the study of computer algorithms that can learn and develop on their own through experience and data (Mitchell, 1997). It is becoming one of the hottest topics for research. Researchers are used ML in various areas such as health, energy, biology, social science, banking, etc. ML helps to detect some diseases earlier, predict energy consumption, forecast sales in various sectors, identification of fraud or spam e-mail, and recommend products or videos.

As examples in the energy sector, Ağbulut (2022), Ayvaz et al. (2017), and, Sun and Liu (2016) used ML to forecast energy demand and CO_2 emission in different models. In the health sector, Yang et al. (2022) studied the prediction of lung cancer recurrence and survivability, and Chowdhury et al. (2022) studied the diagnosis of COVID-19 from coughs sounds, Sabeti, and friends (2022) searched for detection of craniosynostosis in newborns with machine learnings. Madhurya et al. (2022), and Şahin et al. (2013) examined the detection of credit card fraud with different machine learnings techniques (Ağbulut, 2022; Ayvaz et al., 2017; Chowdhury et al., 2022; Madhurya et al., 2022; Sabeti et al., 2022; Sahin et al., 2013; Sun & Liu, 2016; Yang et al., 2022).

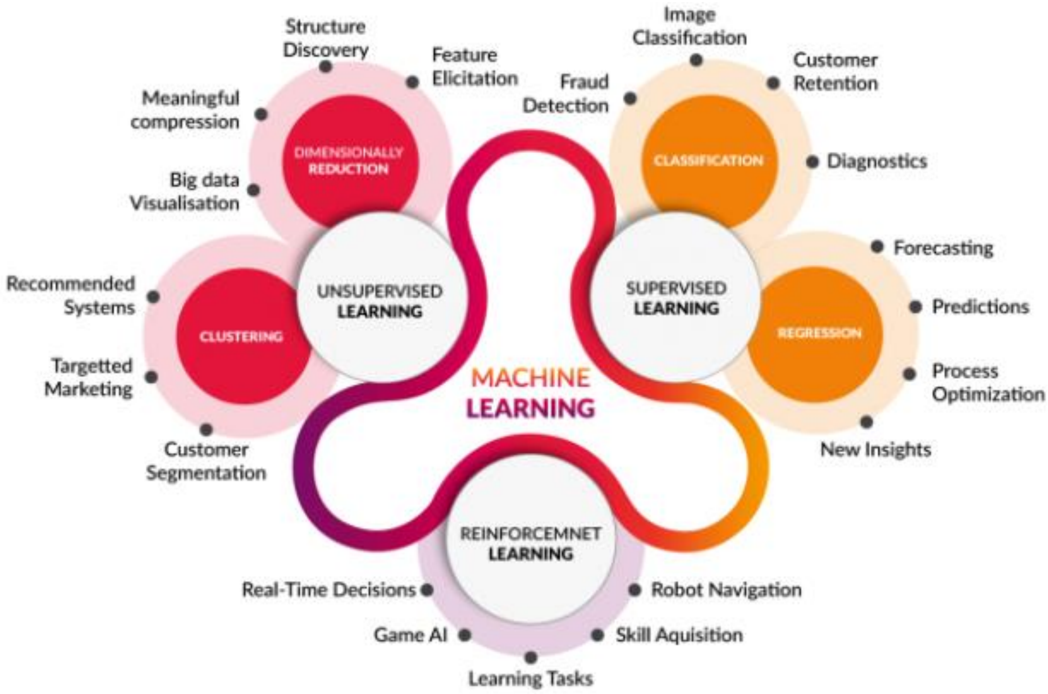

Figure 3.1 Machine learning implementation areas

Note. Adapted from *What Does Machine Learning Mean?* by Ironhack Blog, n.d. (https://www.ironhack.com/en/data-analytics/what-is-machine-learning)

Forecasting future demand is quite important to manage production, plan resources, avoid overstocking, and supply process. There are a number of methodologies that can be used at this point, and most of these methodologies are based on past demand or sales (Rohaan et al., 2022). While Ensafi et al. (2022), used time series forecasting techniques to predict item sales of a retail store, Chen and Ou (2011) used extreme learning machines to forecast sales in the retail industry (Chen & Ou, 2011; Ensafi et al., 2022).

There are various platforms to implement machine learning. In this study, Konstanz Information Miner (KNIME) was used for implementation. KNIME is an open-source and free platform based on Java that used data analysis, integration, and reporting. Figure 3.2 is a summary of input and outputs values used in three regression models. Different models were implemented to sales data and compared with each other. The best prediction was used to explain COVID-19 effects on sales.

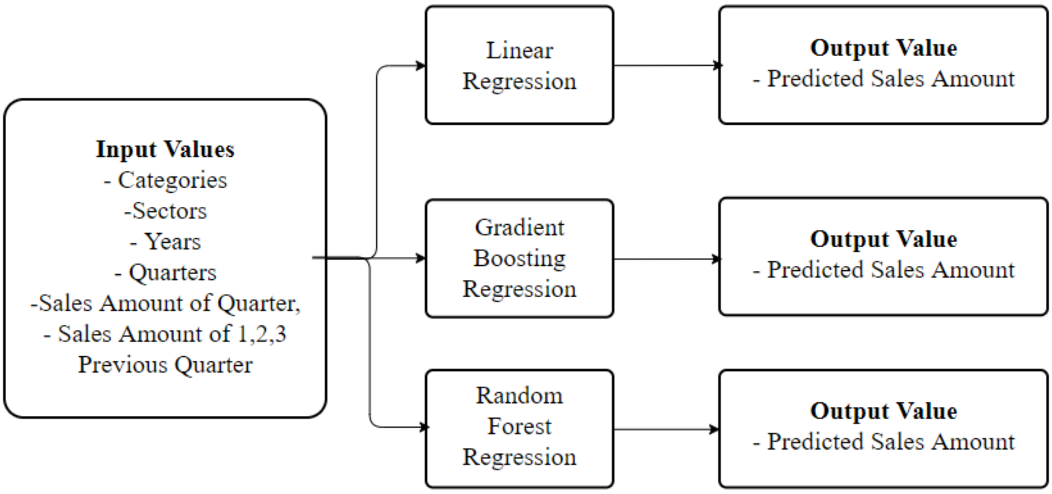

Figure 3.2 Diagram of input and output value

3.2. Data Preparation

In this study, sales data of a technology company was collected between 2015 and 2022 years. At the first, sales data have 3.072 rows that include 8 service categories and 11 sectors. The 3 most known services categories were selected according to sales amount from the 8 services. Since 5 sectors have minor sales amount like 4 percent as total, they were grouped in others. Sales amount was calculated quarterly every year and 1,2, and 3 previous quarter amount was added as new columns to understand sales trends. Every row that has "0" as sales amount was deleted to make more successful forecasting. After preprocessing, sales data have 531 rows. Finally, historical information of COVID-19 was taken from the Republic of Turkey Ministry of Health website (*T.C. Sağlık Bakanlığı*, 2022).

Sales amount normalized with min-max normalization. This method increases consistency of models. The purpose of min-max normalization method is to normalize the smallest value to 0 and the largest value to 1, and spread all other data to this 0-1 range. Its formula is as below.

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

X = The value that will normalized

X_{min} = The smallest value of variable

X_{max} = The biggest value of variable

After normalization, descriptive analysis implemented to sales amount. Normal distribution was controlled and sales amount variables was found non-parametric. Figure 3.3 shows the distribution of values. The outliers that were seen in figure was checked in sales data. They did not remove from data because any mistake was not found.

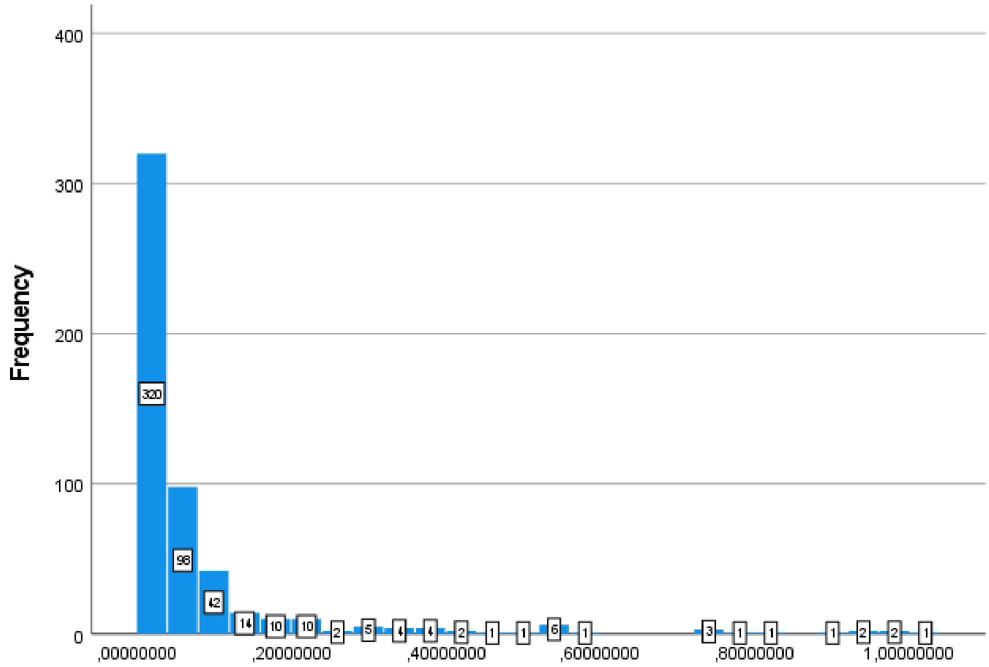

Figure 3.3. Frequency of sales amount

Kruskal Wallis test implemented for category and sector. This method used to test whether the mean of two or more samples shows a significant difference from each other. Table 3.1 shows the results of test. Significance level is lower 0,001, which means category and sector has significance on sales amount.

Table 3.1. Results of Kruskal Wallis test for category and sector

Variables	Test	Significance
Category	Kruskal-Wallis Test	<0,001
Sector	Kruskal-Wallis Test	<0,001

Figure 3.4 is a summary of the total sales amount between 2015 and 2022. The 1st, 2nd, and 3rd service categories have 16,73, 7,92, and, 75,35 sales percentages respectively in total 2015-2022 sales data. 3rd category has the three-fourth sales amount in the last seven years. As sectoral, the technology sector accounts for nearly

half of revenue. Retail, automotive, holding, service, and others have under the 10 percent.

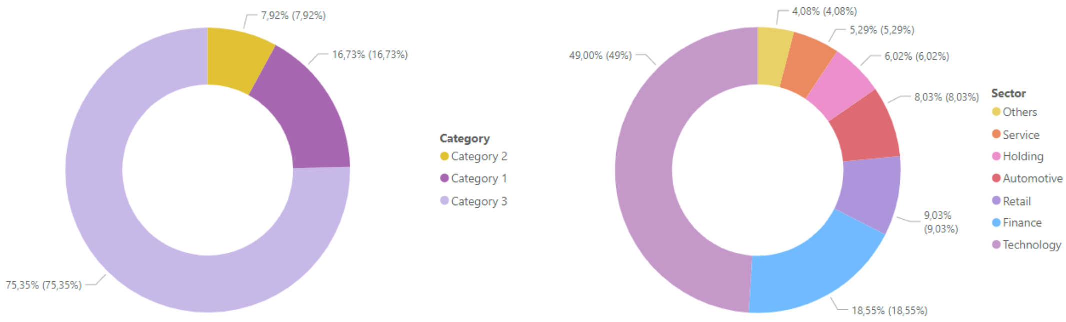

Figure 3.4 Categorical and sectoral sales percentage for 2015-2022 sales amount

Figure 3.5 shows the sales amount of three service categories every quarter. 3rd service category has a major sales percentage every quarter. The revenue line has a significant peak in every last quarter of a year until the 2021 year.

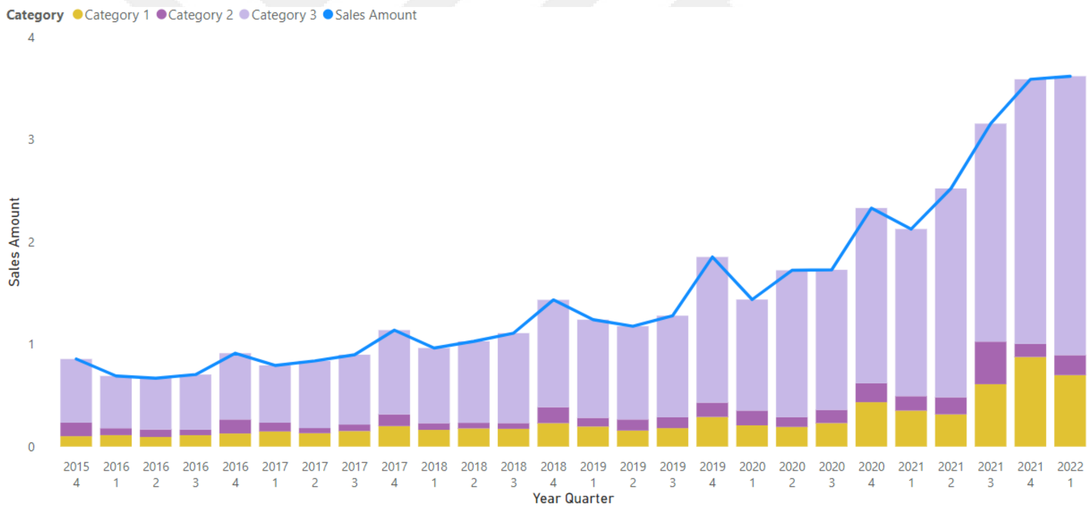

Figure 3.5. Categorical sales amount quarterly

Table 3.2 shows the increase between the first quarter of the years. The predicted increase was calculated using a simple linear regression model. Values from 2015 to 2019 were used in the equation of the regression model. As we can see, the sales rate increases every year according to the regression. In the real data, there is a deviation for the first quarter of 2020, which has COVID -19 in Turkey. However, in the following years, the increase is higher than the calculated value. This can be a positive effect of COVID -19 on this technology company.

Table 3.2 Increase in the first quarters, year over year

Years	Percentage of Increase	According to Regression
2015-2016	7,53%	7,54%
2016-2017	14,49%	14,51%
2017-2018	21,57%	21,48%
2018-2019	28,40%	28,45%
2019-2020	14,86%	35,42%
2020-2021	49,20%	42,39%
2021-2022	69,91%	49,36%

3.3. Machine Learning Models

Prepared sales data splits as train and test data. Train data is the dataset on which the model is trained. Test data is a dataset used to evaluate the model developed on a training set. 3 different ML models used on prediction implemented prepared sales data. After implementation root mean squared error (RMSE), mean absolute error (MAE), mean squared error (MSE), mean signed difference (MSD), coefficient of determination (R^2), mean absolute percentage error (MAPE) are calculated.

- The Coefficient of Determination

The coefficient of determination is defined as the fraction of the dependent variable's variance that can be predicted by the independent variables (Wright, 1921). Best value of R^2 is 1 and the worst value is 0. The formula is as follows.

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(Xi-Yi)^2}{\sum_{i=1}^{m}(\bar{Y}-Yi)^2} \quad (2)$$

X_i = Predicted ith value

Y_i = Actual ith value

$\bar{Y}$ = The mean total sum of squares

- The Mean Absolute Error (MAE)

The MAE is the average of the absolute error values. Each error affects MAE in direct proportion to the absolute value of the error (Pontius et al., 2008). While the best value is zero the worst value is +∞. The formulation is as follows.

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|Xi - Yi| \quad (3)$$

- The Mean Squared Error (MSE)

The Mean Squared Error is a measure of the quality of a predicator (Bickel & Doksum, 2015). Its best value is 0 and worst value is +∞. The formula is as follows.

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(Xi - Yi)^2 \quad (4)$$

- The Root Mean Squared Error (RMSE)

The Root Mean Squared Error (RMSE) is a metric for calculating the discrepancies between expected and observed values. The RMSE is sensitive to outliers (Pontius et al., 2008). The best and worst value like the mean squared error. The formulation is as below.

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(Xi - Yi)^2} \quad (5)$$

- The Mean Signed Difference (MSD)

The Mean Signed Difference is a sampling statistic that summaries how well a set of estimates matches the quantities they are supposed to estimate. While the best value is zero the worst value is +∞. The following is the formula.

$$MSD = \frac{1}{n}\sum_{i=1}^{n}\hat{\theta}i - \theta i \quad (6)$$

$\theta\hat{I}$ = The predicted value of a series at lead time

θ_I = The actual value in that time point

- The Mean Absolute Percentage Error (MAPE)

In statistics, the Mean Absolute Percentage Error is a measure of a forecasting method's prediction accuracy. It is not appropriate for models with substantial predicted errors (Armstrong & Collopy, 1992). Its best value is 0 and worst value is +∞. The formula is as follows.

$$MAPE = \frac{1}{m}\sum_{i=1}^{m}\frac{|Yi - Xi|}{|Yi|} \quad (7)$$

A study by Chicco and friends shows that R^2 has more advantages over other statistical rates such as MAE, MSE, RMSE, and MAPE in different analyses.

According to the study, only MAPE or MSE, or RMSE is not enough to explain a regression performance quality (Chicco et al., 2021). In this study, models are compared to each other according to the R^2 values.

3.3.1. Linear Regression

Linear regression is a classical statistical algorithm and a machine learning algorithm. The first type of regression analysis was developed by Adrien Marie Legendre in 1806 (Legendre, 1806). The relationship between variables is modeled using linear predictor functions. Simple linear regression is used when there is just one variable. Multiple linear regression is used when there is more than one variable (Rencher & Christensen, 2012). In linear regression, the main goal is finding the best equation which is nearest to the values. Figure 3.6 is an example of linear regression graphics.

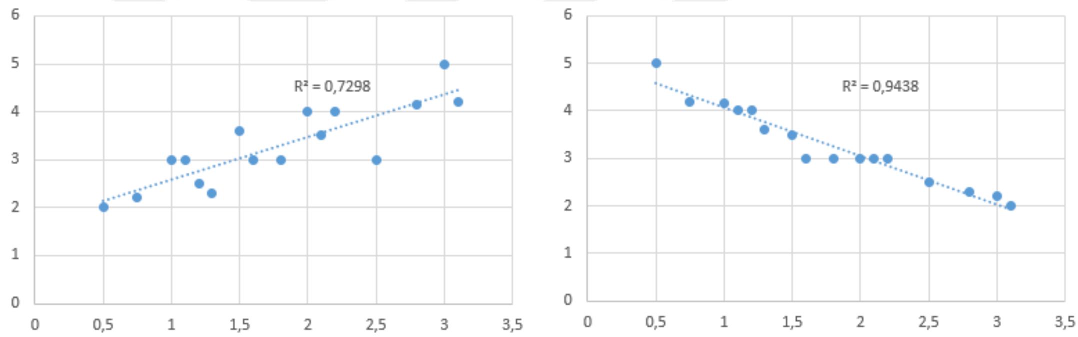

Figure 3.6 Example for linear regression graphics

In linear regression analysis, the coefficient of determination (R^2) is calculated. If the analysis is correct, this value must be between 0 and 1. The goodness of fit is more successful if the R^2 value is near 1.

3.3.2. Gradient Boosting Trees Regression

The gradient boosting technique used in classification and regression was suggested by Breiman et al. in 1984 (Breiman et al., 1984). The gradient-boosting algorithm improved weak learners to strong learners (Nie et al., 2021). The main goal is to minimize the sum of squared errors. Figure 3.7 shows the relationship between iterations and error. With iteration, the error is decreasing and the model becomes more successful.

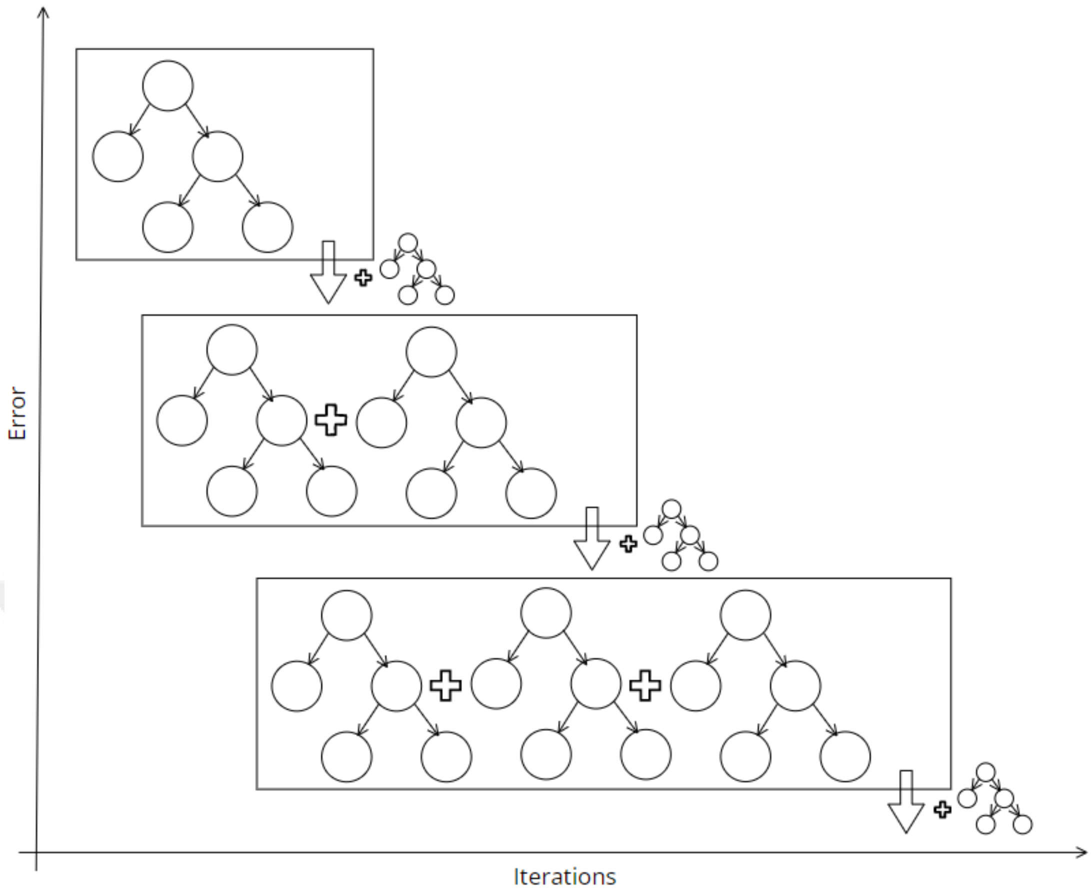

Figure 3.7 Schematic representation of gradient boosting regression

3.3.3. Random Forest Regression

Like gradient boosting, the random forest technique is used for classification and regression. Tin Kam Ho created the first algorithm in 1995 (Ho, 1995). The random forest algorithm generates reasonable forecasting with little configuration. In the regression model, the mean and average forecasting of each tree are returned and overfitting of the training set is prevented (Ho, 1998; Minasny, 2009). Figure 3.8 shows the diagram of random forest regression. This method is very popular to analyze large data sets (Borup et al., 2022).

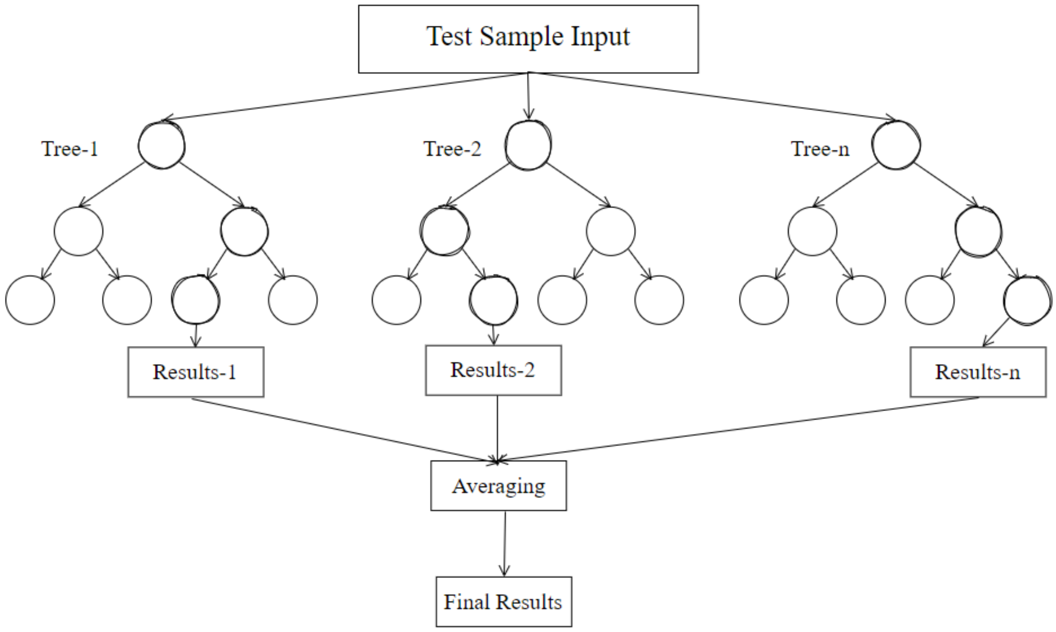

Figure 3.8 Diagram of random forest regression

4. IMPLEMENTATION

Sales were calculated quarterly each year and the amounts of the 1, 2, and 3 previous quarters were added as new columns to understand sales trends. Three service categories,7 sectors, years and quarterly knowledge, quarterly revenue amounts, and sales amount of 1,2, and 3 previous quarters are used as inputs for machine learning. After splitting the sales data into training and test data, three regression models were implemented and the sales figures for the next year were predicted with different year combinations.

Three regression models were constructed using KNIME. Figure 4.1 shows the construction of the models. Excel reader module is used to import collected sales data. KNIME understands data type automatically but also allows to change manually. The imported data were sorted by year and quarter. With the normalizer module, data consistency increased for sales amount. The partitioning module helps to split data as train and test. Partitioning rate change according to the years which belongs to the train or test. Three regression model is added with two modules that are learner and predictor. The learner module teaches machine learning which data are input and which are predicted. The predictor module is configured to predict sales amounts. The numeric scorer calculates the success of models and the line plot shows custom graphics.

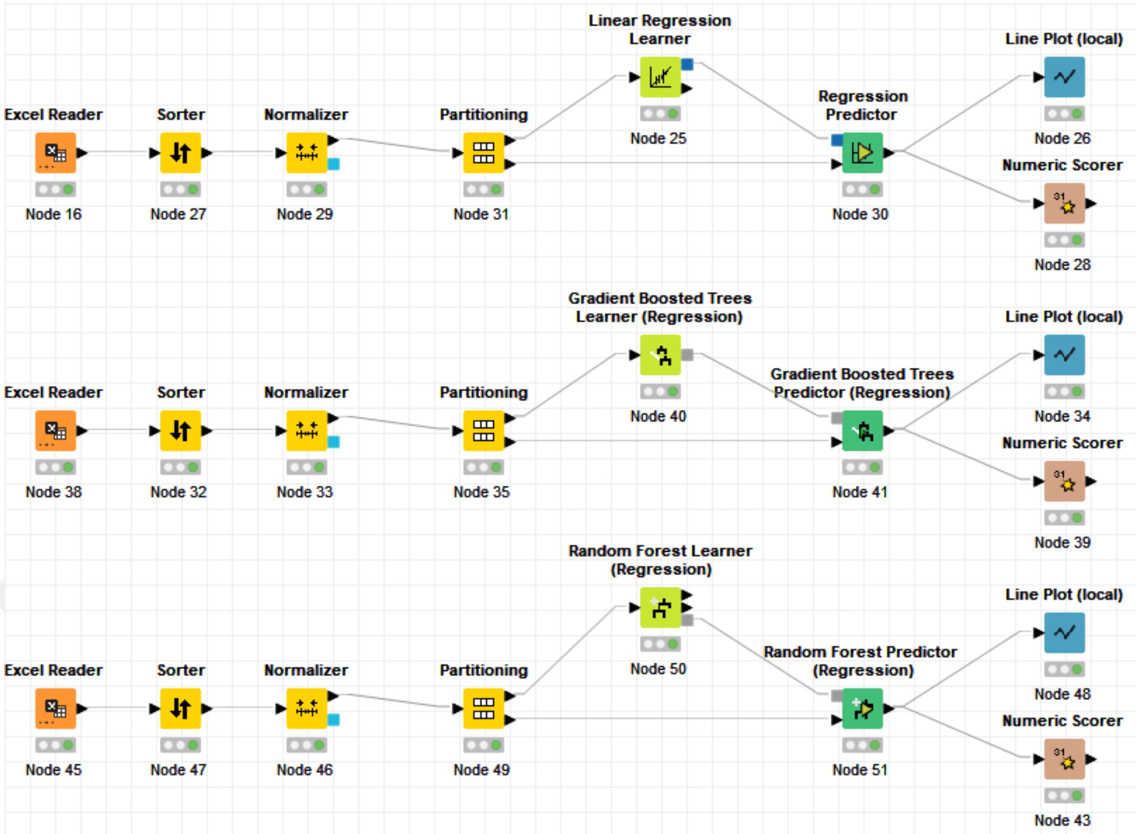

Figure 4.1 Regression models on KNIME

5. NUMERICAL RESULTS

In this section, three various forecastings were calculated with KNIME. One of them belongs to pre COVID-19 era and the others prediction of the COVID-19 era.

5.1. Forecast for 2019 with Data Between 2015 and 2018

From 2015 to 2018 years belong to the pre-COVID-19 era. Data from 2015-2018 were used as training data and data from 2019 were used as test data. The sales data has 270 rows for training and 82 rows are predicted with three models. Figure 5.1 shows the predicted sales amount with linear regression and the actual sales amount for all sectors in 2019. Even if the quality of prediction looks good, it changed from sector to sector.

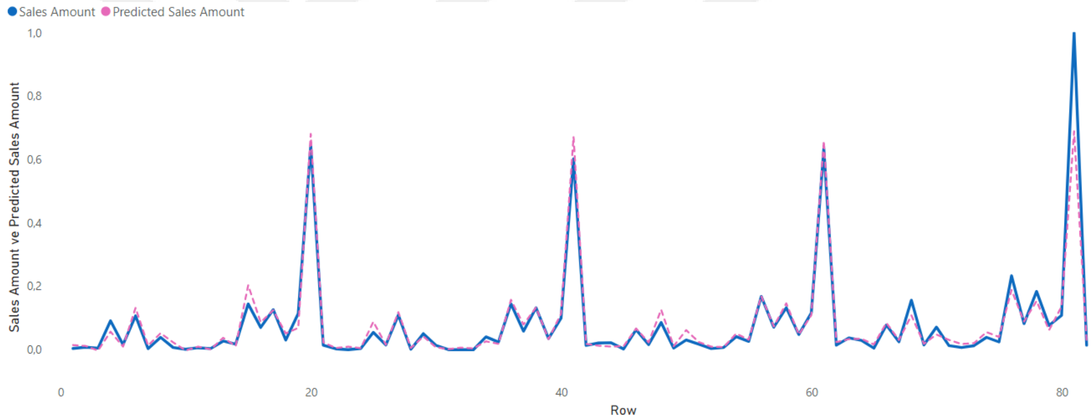

Figure 5.1 Actual and predicted sales amount of 2019 year with LR for all sectors

Figure 5.2 and 5.3 details the actual and projected sales amounts for the technology and holding sector. There is a noticeable deviation at the end of the year. There may be delays in the collection of revenues.

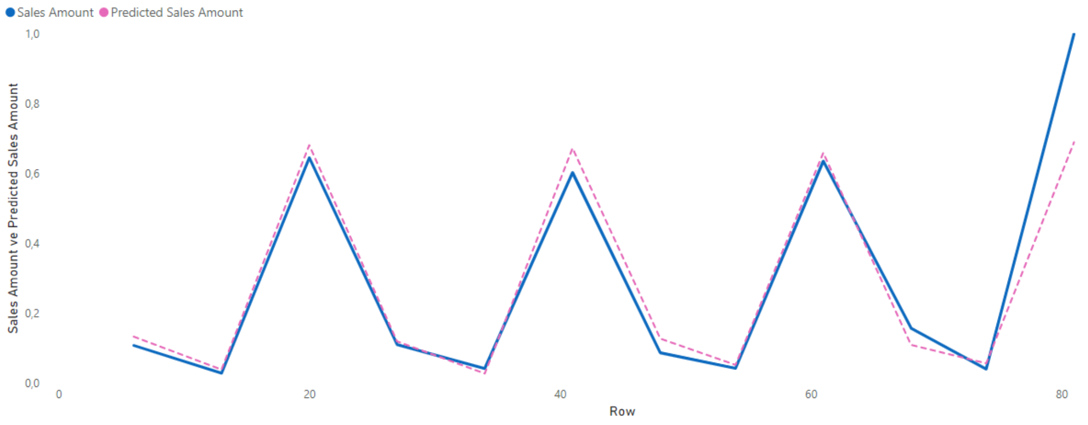

Figure 5.2 Actual and predicted sales amount of 2019 year with LR for technology sector

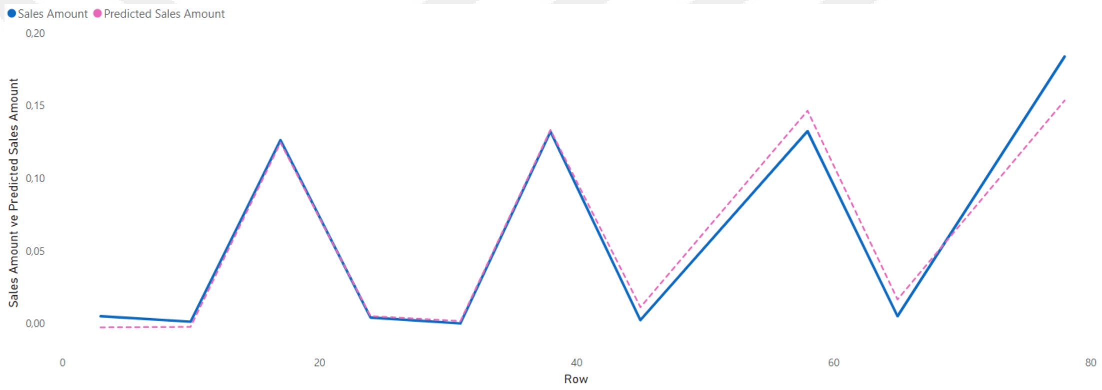

Figure 5.3 Actual and predicted sales amount of 2019 year with LR for holding

When we looked automotive sector in Figure 5.4, there was a difference in the first and second quarters of the year. While actual sales amount is more than predicted in the first quarter, it is opposite during the second quarter.

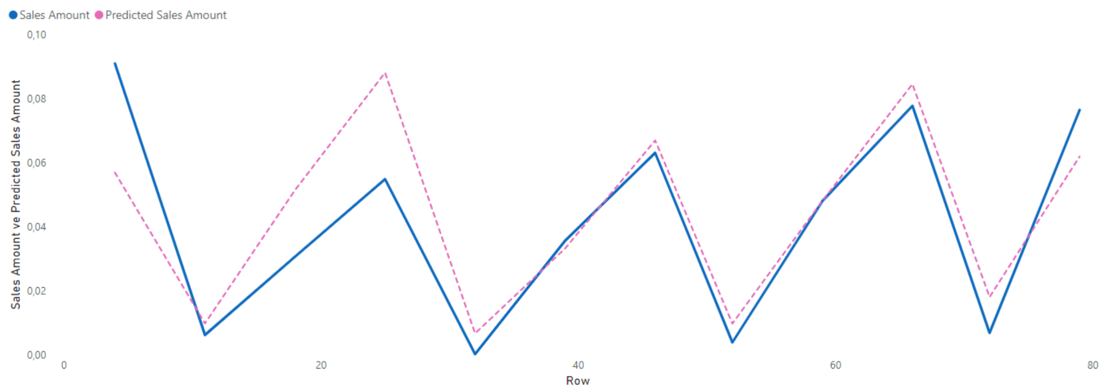

Figure 5.4 Actual and predicted sales amount of 2019 year with LR for automotive sector

The finance sector had a difference between actual and predicted sales amount almost all year is shown in Figure 5.5. While predicted sales amount was more than actual in the first quarter, there was not a difference in the second quarter. This means the collection revenue is not associated with this difference.

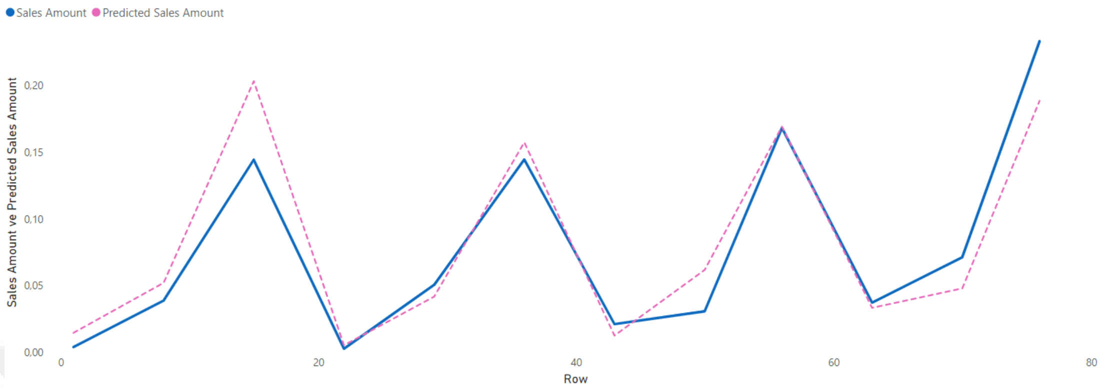

Figure 5.5 Actual and predicted sales amount of 2019 year with LR for finance sector

Figure 5.6 explains the values of the retail sector. There is a significant difference in the first quarter of the year like the finance sector. However, in this case, this difference is a positive way.

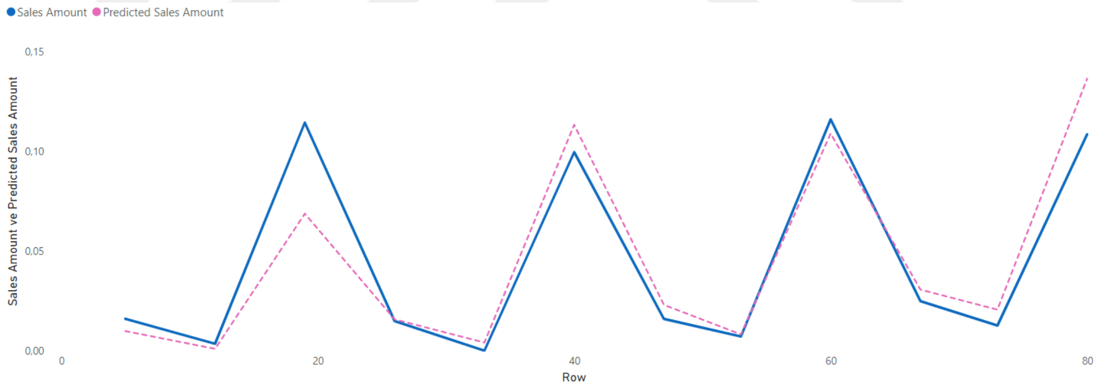

Figure 5.6 Actual and predicted sales amount of 2019 year with LR for retail sector

Service and others were shown in Figures 5.7 and 5.8. Both of them had significant deviations all year. It is hard to explain this difference with a collection of revenue. Because of the irregularity of sales amount, different models can be improved for those sectors.

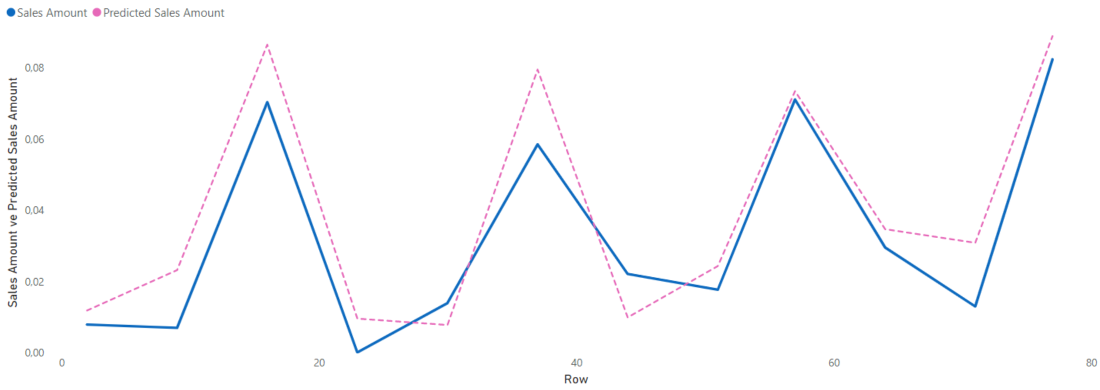

Figure 5.7 Actual and predicted sales amount of 2019 year with LR for service sector

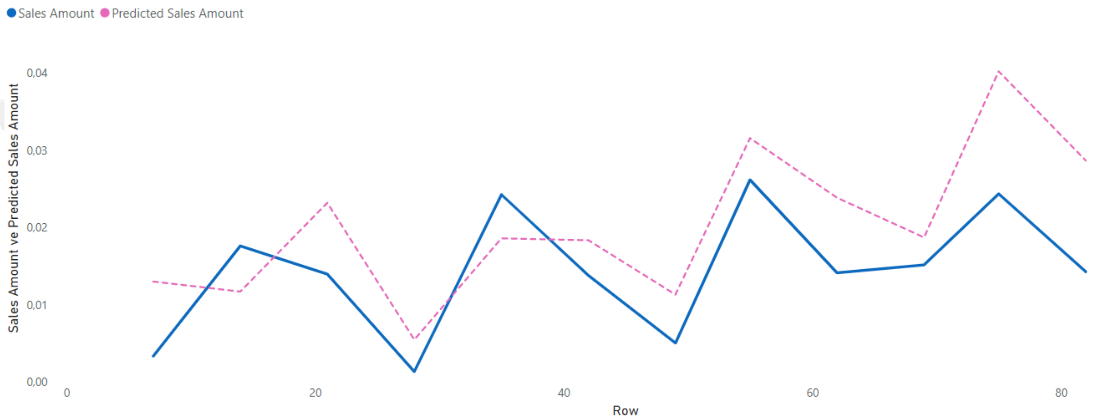

Figure 5.8 Actual and predicted sales amount of 2019 year with LR for others

Table 5.1 is a summary of the results of three regression models. Results shows, that while linear regression has the biggest R^2 value which means has better goodness of fit, random forest regression is the most ineffective regression model.

Table 5.1 Result of three regression models for 2019 forecasting

Regression Model	Train Data	Test Data	R^2	MAE	MSE	RMSE	MSD	MAPE
LR	2015-2018	2019	0,938	0,017	0,002	0,039	0,001	4,191
GBR			0,933	0,017	0,002	0,041	-0,005	3,849
RFR			0,893	0,019	0,003	0,052	-0,009	4,915

5.2. Forecast for 2020 with Data Between 2015 and 2019

The First COVID-19 case has announced at the beginning of 2020 in Turkey. We try to forecast the 2020 year that has COVID-19 with data between 2015 and 2019. The construction of regression models is the same as 2019 forecasting which is explained in the implementation section. 352 rows of sales data were used for training and 80 rows were predicted. The actual and predicted sales amount was shown in Figure 5.9.

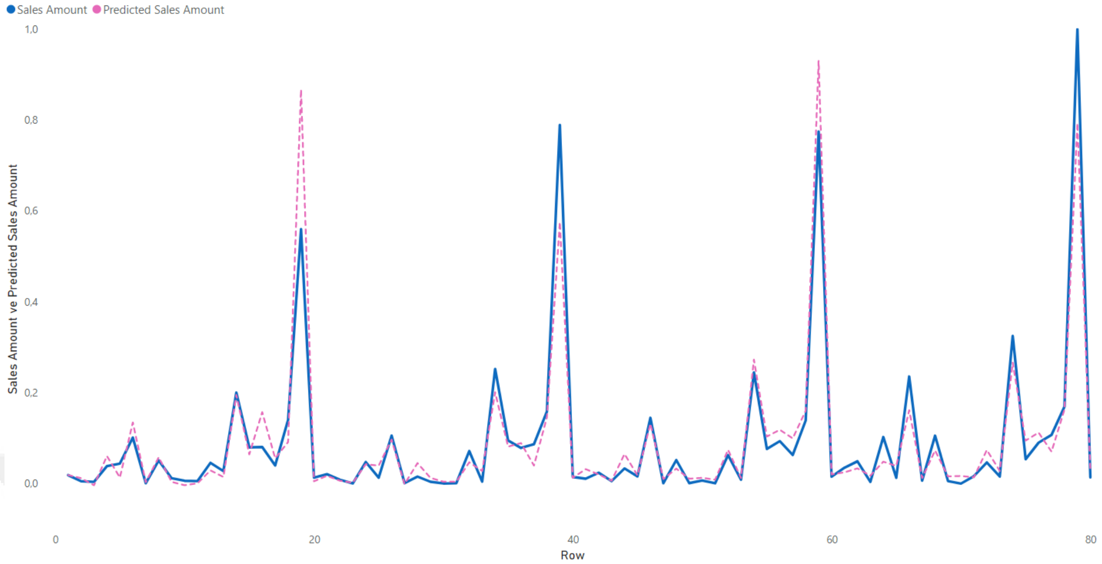

Figure 5.9 Actual and predicted sales amount of 2020 year with linear regression

It seems that the actual sales amount is lower than the predicted sales amount in the first quarter of 2020. Figure 5.10 shows the detail of the first quarter. As we understand, there is a notable variation in category 3 that has the biggest sales value. The first quarter revenue is lower than the predicted sales amount.

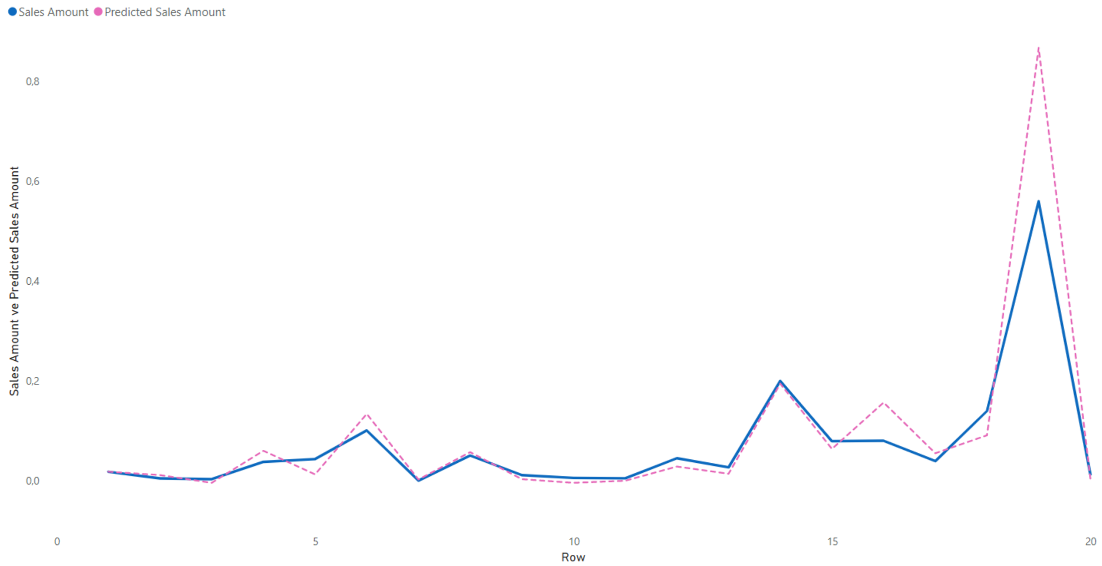

Figure 5.10 Actual and predicted sales amount of Q1 2020 year with linear regression

When on closer inspection of the second quarter in Figure 5.11, we can see total sales amount is bigger than predicted. The deficit in the first quarter may have been offset here.

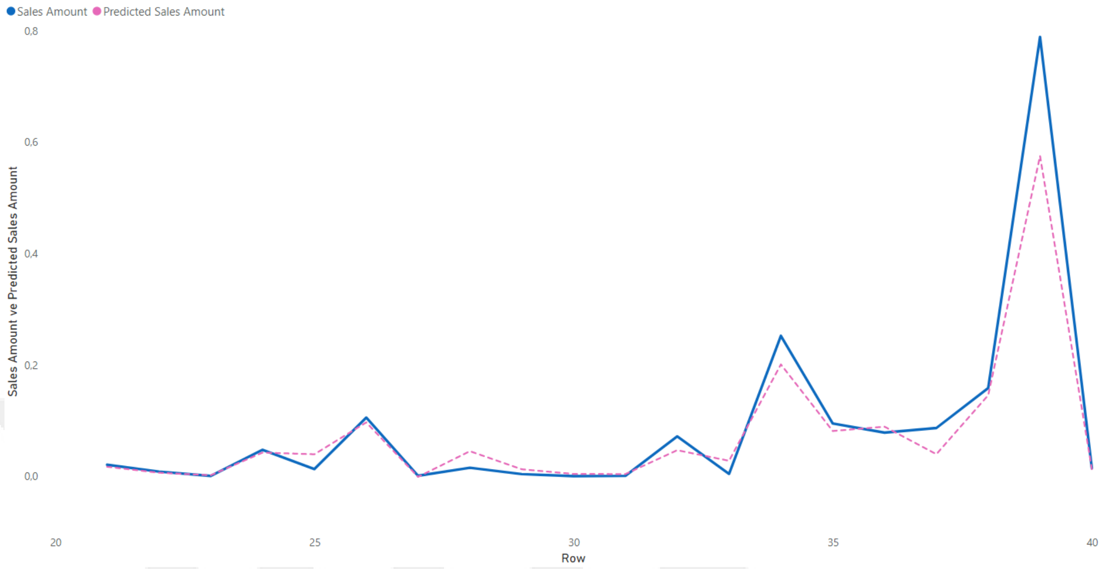

Figure 5.11 Actual and predicted sales amount of Q2 2020 year with linear regression

The third quarter of the year has better accuracy as we can see in Figure 29 when compared first and second quarters. This adaptation impact is kept in the fourth quarter which is shown in Figure 5.12.

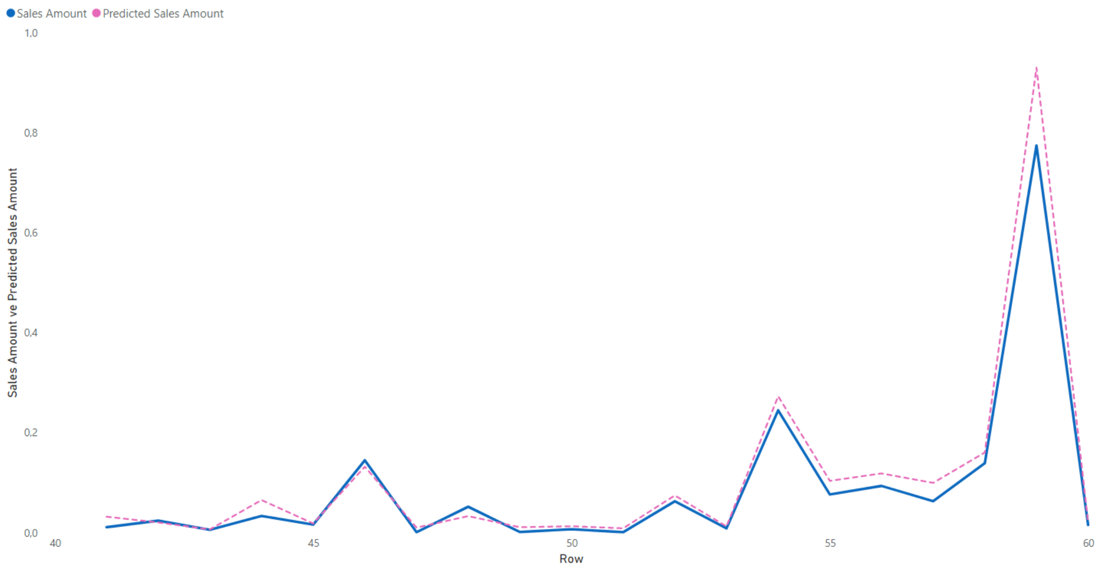

Figure 5.12 Actual and predicted sales amount of Q3 2020 year with linear regression

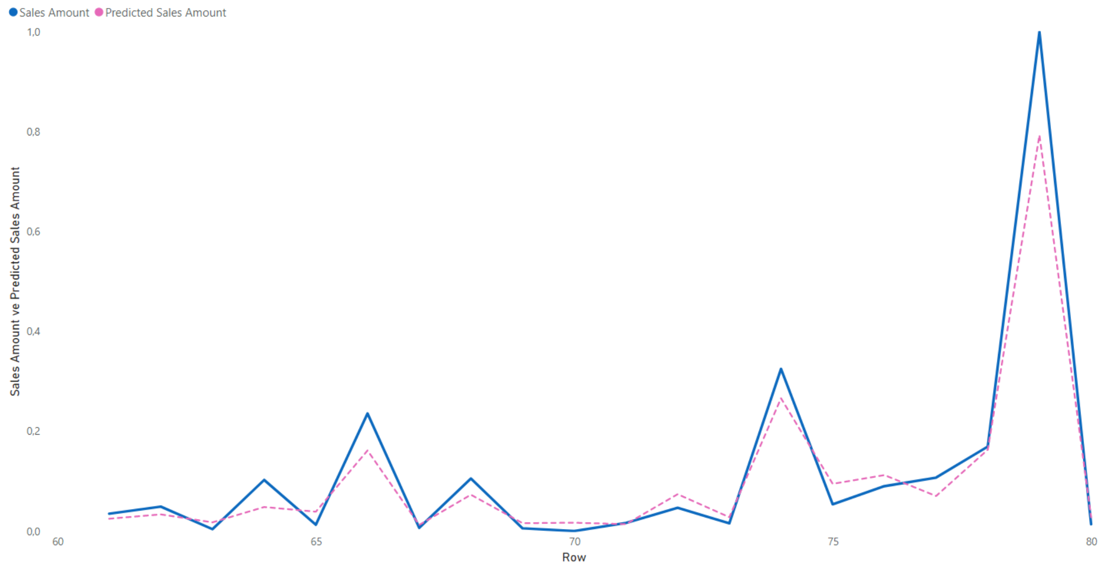

Figure 5.13 Actual and predicted sales amount of Q4 2020 year with linear regression

Table 5.2 shows that R^2 has decreased compared to the 2019 prediction. COVID - 19 may cause this decrease.

Table 5.2 Results of three regression models for 2020 forecasting

Regression Model	Train Data	Test Data	R^2	MAE	MSE	RMSE	MSD	MAPE
LR	2015-2019	2020	0,896	0,028	0,003	0,056	0,001	2,108
GBR			0,928	0,023	0,002	0,047	-0,009	1,093
RFR			0,894	0,026	0,003	0,057	-0,013	1,757

The linear regression model was the best model when we predict the non-COVID-19 era. The linear regression was implemented quarterly for the 2020 year. Results are written in table 5.3. As we understand, prediction quality gets better towards the end of the year. Especially, the R^2 value of the 1st quarter has a disruptive impact on the year. When R^2 is calculated with the 2nd, 3rd, and 4th quarters, the best value has been obtained. The first case of COVID-19 was appeared end of 2019 and announced as a pandemic in March 2020. In Turkey, the full lockdown was from March to June. This situation explains the lower R^2 value in the first and second quarters. Until 21st November, Turkey did not have a lockdown.

Table 5.3 Results of linear regression quarterly in the 2020 year

Regression Model	Train Data	Test Data	R^2
LR	2015-2019	1^{st} Quarter	0,42
LR		1^{st},2^{nd} Quarter	0,778
LR		1^{st},2^{nd},3^{rd} Quarter	0,841
LR		2^{nd},3^{rd},4^{th} Quarter	0,931

5.3. Forecast for 2020-2021 with Data Between 2015 and 2019

The sales data between 2015 and 2019 were used to predict the 2020 and 2021 years which has pandemic. 352 rows of sales data were used for training and 158 rows were predicted. The line graph of actual and predicted sales data is given in figure 5.14.

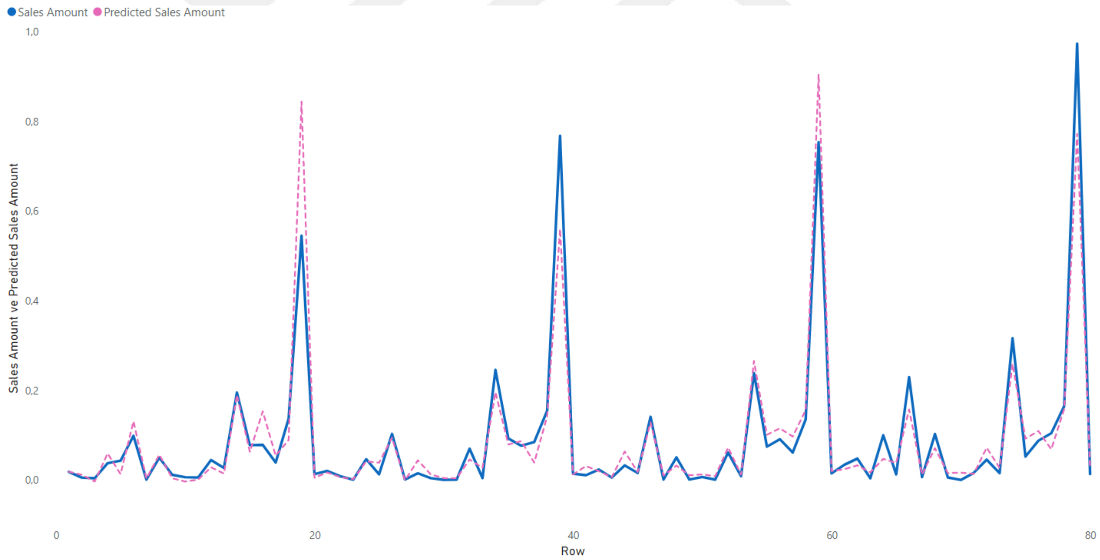

Figure 5.14 Actual and predicted sales amount of 2021 year with linear regression

Table 5.4 shows the statistical rates of each regression model. According to the results, linear regression has the best value and is better when compared to forecasting 2020. This improvement can be proof that after the first year of COVID-19 normalization process started.

Table 5.4 Results of three regression models for 2020-2021 forecasting

Regression Model	Train Data	Test Data	R^2	MAE	MSE	RMSE	MSD	MAPE
LR	2015 - 2019	2020 - 2021	0,921	0,033	0,003	0,058	-0,003	1,459
GBR			0,832	0,039	0,007	0,084	-0,021	0,874
RFR			0,839	0,039	0,007	0,083	-0,028	1,074

When the actual and predicted total sales amount in 2020 was compared predicted value is lower than actual. It can be a negative effect of COVID-19 at the beginning of the 2020 year. When collection data examined, the first quarter of 2020 has missing collection. There may have been a problem in collection due to the uncertainty brought by the COVID-19 period. However, in 2020 there is a positive effect on the total sales amount. Table 5.5 is a summary of the difference between actual and predicted sales amounts.

Table 5.5 The difference between actual and predicted total sales amounts

Year	Quarter	Actual Total Sales Amount	Predicted Total Sales Amount	Difference
2020	Q1	1,44	1,73	-20,48%
	Q2	1,72	1,45	15,74%
	Q3	1,73	2,09	-20,69%
	Q4	2,33	2,03	12,87%
2021	Q1	2,13	2,32	-8,99%
	Q2	2,52	2,18	13,64%
	Q3	3,16	2,90	8,21%
	Q4	3,59	3,47	3,45%

5.4. Forecast for 2021 with Data Between 2015 and 2020

By using the values between 2015-2020, 2021 values were tried to be predicted. 432 lines belong to train data and 78 lines are predicted as sectoral. Table 5.6 summarized metrics of three regression models. Linear regression has the best R^2 value.

Table 5.6 Results of three regression models for 2021 forecasting

Regression Model	Train Data	Test Data	R^2	MAE	MSE	RMSE	MSD	MAPE
LR	2015-2020	2021	0,928	0,039	0,004	0,063	-0,012	0,752
GBR			0,912	0,041	0,005	0,069	-0,023	0,596
RFR			0,889	0,043	0,006	0,078	-0,033	0,518

2020 year was the most affected from COVID-19. 2021 values predicted with two different train data for understanding that 2020 data has disruptive effect on machine learning whether or. Table 5.7 shows the R^2 value of two different models. The coefficient of determination has better value without 2020 sales data. To ensure that the 2020 sales data will be ignored, the model can be run again by continuing to collect data after the COVID-19.

Table 5.7 Comparison of 2021 R^2 values with different train data

Regression Model	Train Data	Test Data	R^2
LR	2015-2019	2021	0,933
LR	2015-2020	2021	0,928

6. CONCLUSION

After COVID-19 first appeared in China, various sectors were affected tourism, accommodation, education, aviation, production, automotive, energy, technology, and food. Every country took various cautions like using masks, remote working, and curfews to control this pandemic.

Remote working and curfews affected the demand for information and communication technologies (ICT). People need to do various things online such as shopping, working, studying and ICT makes them possible. That’s why companies investing in digitalization for adopting this period.

This study aims to understand the impact of COVID -19 on a Turkish consulting firm in the technology sector with different machine learnings models and try to understand popularity of information technologies.

Results show COVID-19 has adverse effects, especially in the first quarter of the 2020 year. After the adaptation period, the sales amount normalizes. Even, in 2021 a positive effect was seen on sales amount. Further, it can be investigated whether the machine learning model tested afterward is suitable for predicting future years or whether it is more appropriate to make predictions by ignoring the COVID-19 period. In addition, the inflation impact can be studied during the COVID-19 era, and sales revenue convert as dollars because of changes in currency. With the increasing demand for the technology sector, being a developer is more interesting day by day, and companies seeking good developers in Turkey and also around the world. It can be examined as a new study, impacts of increasing demand for information technologies on developers, and their salary.

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