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Fleet Type Planning for Private Airline Transportation After Covid-19

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Anahtar Kelimeler

Özel Havayolu Taşımacılığı
Filo Türü Planlama
Makine Öğrenmesi
DVM
GSR
Topluluk Öğrenme
Regresyon Ağaçları

Graphical/Tabular Abstract (Grafik Özet)

In this study, the number of aircraft types was estimated using the attributes determined for a private airline company, and it is given as a graphical summary below. / Bu çalışmada özel bir havayolu şirketi için belirlenen öznitelikler kullanılarak uçak türü sayısı tahmini yapılmıştır ve aşağıda grafiksel özet olarak verilmiştir.

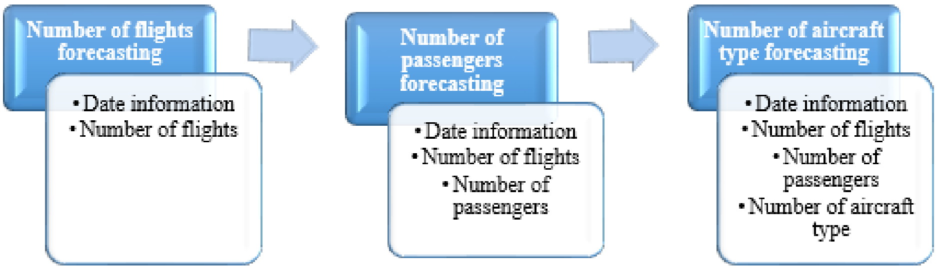

Figure A. *The areas where the forecast work is applied and the features used /* ***Şekil A.*** *Tahmin çalışmasının uygulandığı alanlar ve kullanılan özellikler*

Highlights (Önemli noktalar)

- *A forecast study using machine learning methods was conducted to provide accurate flight schedules for a private airline company in the future. / Gelecekte özel bir havayolu şirketi için doğru uçuş programları sağlamak üzere makine öğrenimi yöntemleri kullanılarak bir tahmin çalışması yapılmıştır.*
- *Support Vector Machines, Gaussian Process Regression, Regression Trees, and Ensemble Learning models were compared for the forecasting study. / Tahmin çalışması için Destek Vektör Makineleri, Gauss Süreci Regresyon, Regresyon Ağaçları ve Ensemble Öğrenme modelleri karşılaştırılmıştır.*
- *The number of flights is found to increase by approximately 7% in 2022 compared to the pre-pandemic period. / 2022 yılında uçuş sayısının pandemi öncesine göre yaklaşık %7 arttığı tespit edilmiştir.*

Aim (Amaç): *This study aimed to forecast future flight schedules for a private airline company, given the impact of the COVID-19 pandemic on air transportation. / Bu çalışma, COVID-19 salgınının hava taşımacılığı üzerindeki etkisi göz önüne alındığında, özel bir havayolu şirketi için gelecekteki uçuş programlarını tahmin etmeyi amaçlamıştır.*

Originality (Özgünlük): *This study uses machine learning to forecast future flight schedules for a private airline company, providing valuable insights for strategic planning and decision-making in the industry. The analysis of COVID-19's impact on air transportation and the application of advanced analytical techniques demonstrate the potential for future research in aviation. / Bu çalışma, özel bir havayolu şirketinin gelecekteki uçuş programlarını tahmin etmek için makine öğrenimini kullanmakta ve sektörde stratejik planlama ve karar verme için değerli bilgiler sağlamaktadır. COVID-19'un hava taşımacılığı üzerindeki etkisinin analizi ve gelişmiş analitik tekniklerin uygulanması, havacılıkta gelecekteki araştırmaların potansiyelini göstermektedir.*

Results (Bulgular): *Contrary to commercial airlines, private airline transportation showed an increase in customer demand due to the minimization of personal contact. In addition, results predict a 7% increase in the number of flights in 2022 compared to the pre-pandemic period. / Ticari havayollarının aksine özel havayolu taşımacılığı, kişisel temasın en aza indirilmesi nedeniyle müşteri talebinde artış göstermiştir. Ayrıca sonuçlar, 2022 yılı için uçuş sayısında pandemi öncesine göre %7'lik bir artış öngörmektedir.*

Conclusion (Sonuç): *This study provides insights for fleet planning using machine learning methods to predict future flight schedules for a private airline company and contributes to the air transport industry. / Bu çalışma, özel bir havayolunun şirketinin gelecekteki uçuş programlarını tahmin etmek için makine öğrenimi yöntemlerini kullanarak filo planlaması için içgörü sağlar ve hava taşımacılığı endüstrisine katkıda bulunmaktadır.*

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Abstract

The global impact of the COVID-19 pandemic has done great damage to air transportation. Demand for airline transportation has declined for reasons such as quarantine practices by countries, curfews, the economic recession, and the transfer of meetings to digital platforms. This situation has also led to a change in individuals' preferences for air transport. The most noticeable change in air transport is the tendency of individuals to use air transport privately to minimize the health risks that face-to-face contact can pose. Individuals who avoid commercial air transport where public transportation is available have shifted to private airline transportation. For these reasons, a forecast study was conducted in this study so that a private airline could provide accurate flight schedules in the future. For the forecast study, the number of aircraft types for 2022 was determined by obtaining data on the number of aircraft by passenger capacity, the number of flights, and the number of passengers for 2019-2021 from the airline company. Support Vector Machines (SVM), Gaussian Process Regression (GPR), Regression Trees, and Ensemble Learning models from machine learning methods were used for the forecasting study. The performance evaluation of the models used was compared. The model results with the highest performance evaluation were used. According to the results obtained, it has been found that there will be an increase of approximately 7% in the number of flights for 2022 compared to the pre-pandemic period. The findings provided important information for the company's future fleet planning.

Covid-19 Sonrası Özel Havayolu Taşımacılığı İçin Filo Türü Planlaması

Makale Bilgisi

Araştırma makalesi
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Öz

COVID-19 salgınının küresel etkisi hava taşımacılığına büyük zarar vermiştir. Ülkelerin karantina uygulamaları, sokağa çıkma yasakları, ekonomik durgunluk, toplantıların dijital platformlara taşınması gibi nedenlerle havayolu taşımacılığına olan talep azalmıştır. Bu durum bireylerin hava taşımacılığına yönelik tercihlerinin de değişmesine neden olmuştur. Hava taşımacılığındaki en dikkat çekici değişim, bireylerin yüz yüze temasıyla oluşabilecek sağlık risklerini en aza indirmek için hava taşımacılığını özel olarak kullanma eğilimidir. Toplu taşımanın mevcut olduğu yerlerde ticari hava taşımacılığından kaçınan bireyler, özel havayolu taşımacılığına yönelmiştir. Bu nedenlerle, bu çalışmada özel bir havayolu şirketinin gelecekte doğru uçuş programları sağlayabilmesi için bir tahmin çalışması yapılmıştır. Tahmin çalışması için havayolu şirketinden 2019-2021 yılları için yolcu kapasitesine göre uçak sayısı, uçuş sayısı ve yolcu sayısı verileri temin edilerek 2022 yılı için uçak tipi sayısı belirlenmiştir. Tahmin çalışması için makine öğrenmesi yöntemlerinden Destek Vektör Makineleri (DVM), Gauss Süreç Regresyonu (GSR), Regresyon Ağaçları ve Topluluk Öğrenme modelleri kullanılmıştır. Kullanılan modellerin performans değerlendirmesi karşılaştırılmıştır. En yüksek performans değerlendirmesine sahip model sonuçları kullanılmıştır. Elde edilen sonuçlara göre 2022 yılı için uçuş sayılarında pandemi öncesi döneme göre yaklaşık %7'lik bir artış olacağı tespit edilmiştir. Bulgular, şirketin gelecekteki filo planlaması için önemli bilgiler sağlamıştır.

1. INTRODUCTION (GİRİŞ)

Nowadays, air transport is frequently used by millions of people because it offers significant advantages compared to other means of transport, such as safety, reliability, comfort, accessibility, and speed. Developments in information and communication technology infrastructure, factors influencing supply and demand, the search for competition, and differentiation in individual behavior are increasing interest in air transportation. The use of air transport, especially for business travel, makes it one of the most important components of this sector. The improvement of this system shows that it can significantly affect the development of the aviation industry. Considering

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the current competition in aviation and the factors that influence this sector, this area of study attracts the attention of researchers.

The aviation industry has experienced many crises over the past two decades, each with its own characteristics and economic impact. The COVID-19 pandemic that occurred in 2019 affected many sectors, especially the aviation sector, and caused severe damage. The aviation sector was the sector where countries imposed restriction due to the high number of domestic and international passengers and as the preferred mode of transportation. With the onset of the pandemic, the number of passengers and flights in 2020 fell short of the numbers projected before the pandemic. The number of passengers on international flights between January and April 2020 was about 23 million people in the Americas, 20 million people in Spain, and 18 million people in China. In Turkey, this figure was about nine million people below the projected number [1].

Demand forecasting is a very important issue in the aviation industry. Forecasts are a management tool that companies can use to decide what needs to be done to achieve their goals, and they are an indispensable part of planning. These forecasts, made to eliminate future uncertainties in the daily growing air traffic, ensure that all kinds of problems and requirements are determined in advance. Accurate future forecasts help airline managers plan effectively and efficiently. Forecast results that are high cause demand to exceed supply, while at the same time increasing administrative costs, labour and engineering costs, and other related costs. When forecast results are low, it means there is less demand than supply. In this case, the competence of airline managers is strengthened, which leads to stress and lowers employee motivation [2].

In the aviation industry, forecasting passenger demand is an essential element for airline managers to make appropriate operational plans. With the increasing demand for passengers, the number of flights is also increasing day by day. Forecasting the number of flights for a given period allows the airline to plan future more accurately and save many costs. In addition, many different criteria are considered in the selection of the aircraft type, and the most appropriate aircraft for the fleet structure, planned program, and corporate interests are selected. This selection requires a holistic approach that provides flexibility in fleet planning and operations by addressing the interests of both airlines companies and passengers.

There are numerous studies in the literature on passenger forecasting, flight forecasting, and fleet planning. Some of these studies are as follows: Atay et al. used artificial neural networks and adaptive neuro-fuzzy inference system methods to forecasting passenger demand, cargo demand, and the domestic fleet for the coming years [3]. Efendigil and Eminler analyzed the studies in the literature between 1950 and 2015 on air passenger transportation forecasting according to the technique used, the year and the country. The results showed that the Artificial Neural Network (ANN) method gave the best results [4]. Jiang et al. developed a hybrid approach using a combination of ensemble empirical mode decomposition and gray support vector machine models for short-term high-speed train ridership estimation [5]. Sun et al. developed a new hybrid model called Wavelet-SVM to predict passenger flows in the Beijing subway. They concluded that wavelet-SVM has the best prediction performance compared to the most advanced methods [6]. Jafari used both traditional and artificial intelligence methods to examine the impact of COVID-19 on demand for U.S. domestic passenger demand [7]. Marie-Sainte et al. proposed two new hybrid forecasting methods, particle swarm optimization-based linear regression and firefly algorithm-based linear regression for airline demand forecasting [8]. Dursun and Toraman used the long short-term memory method to forecast the number of passengers at Elazığ Airport. The results showed that the proposed approach helps to forecast the passenger numbers of airlines [9]. Pandit and Akhtar used neural networks in aircraft selection for fleet planning. The model ANN provided a good solution without the time constraints and complexity of the method [10]. Wild et al. compared the performance of some machine learning algorithms with a multiple linear regression model in modeling air transport demand. The results showed that artificial neural networks and neuro-fuzzy inference system methods performed the best [11]. Bao et al. proposed an SVM modeling system based on empirical mode decomposition, which includes a slope-based method for forecasting air passenger traffic. They concluded that the SVM outperforms methods such as Holt-Winters and autoregressive integrated moving average [12]. Guo et al. combined a Copula-based simulation with a regression tree to forecast passenger flows at an airport. The results showed that the presented two-stage forecasting system more accurately predicts both passenger flows and connection times [13]. Laik et al. developed a decision tree for forecasting airline passenger traffic using one year of real data. As a result of the model, a mean square error of 3%-12% was obtained, proving the usefulness of the model in the real world [14]. Wilson and Adams used 96 months of airline passenger data to forecast the number of passengers for 4 years using the GPR method [15].

The purpose of this study is to forecast the number of flights, passenger demand, and number of aircraft types according to passenger capacity for the coming years of a private airline transportation company. Using data on the number of flights, the number of passengers, and the number of aircraft types (0-05, 06-10, 10+ passenger capacity) of airline company, according to weekly passenger numbers were used to determine how many of which aircraft type should be chartered. Machine learning models were used in the study.

2. MATERIALS AND METHODS (MATERYAL VE METOD)

Airline companies use predictive analytics to forecast future customer demand based on information about past travel. Predictive analytics is used to determine the likely future outcome of an event or the probability of a situation occurring [16]. Predictive analytics is a term used mainly in statistical and analytical techniques. This term includes techniques such as statistics, machine learning, data mining, optimization. Predictive analytics forecasts the future by analyzing current and past data [17]. Figure 1 shows the process of predictive analytics. The first step is to collect the raw data. The second step is the section where reporting is organized and data analysis is performed. The third step is the more descriptive part that helps you understand what is going on and identify business issues and opportunities. The fourth step is looking for the answer to the question "What will happen in the future?" by using historical data to predict the future [18].

Airline companies can use past travel information to determine the number of aircraft they will need in the future and plan ahead for their fleet. In this way, they can gain a competitive advantage over other airlines by increasing customer satisfaction in their operations.

2.1. Machine Learning (Makine Öğrenmesi)

Machine learning is self-learning and based on algorithms, i.e., the system learns from experience. In machine learning, the system learns the pattern from the data given to it as input and responds with output to what it learns. It essentially uses a statistical learning algorithm that learns on its own and improves without human intervention [19]. In short, machine learning is one of the fastest growing data-driven technical fields, located at the intersection of computer science and statistics, and is at the core of artificial intelligence and data science [20]. The rapid adoption of machine learning methods that leverage Big Data in technology, science, and commerce is leading to more evidence-based decision making in many different fields such as healthcare, manufacturing, education, financial modeling, military, and marketing [21]. Machine learning has become one of the preferred methods among researchers in recent years to intelligently analyze data and finding solutions to complex real-world problems. There are many machine learning methods such as SVM, decision trees, Bayesian learning, k-means clustering, association rule learning, regression, and neural networks [22].

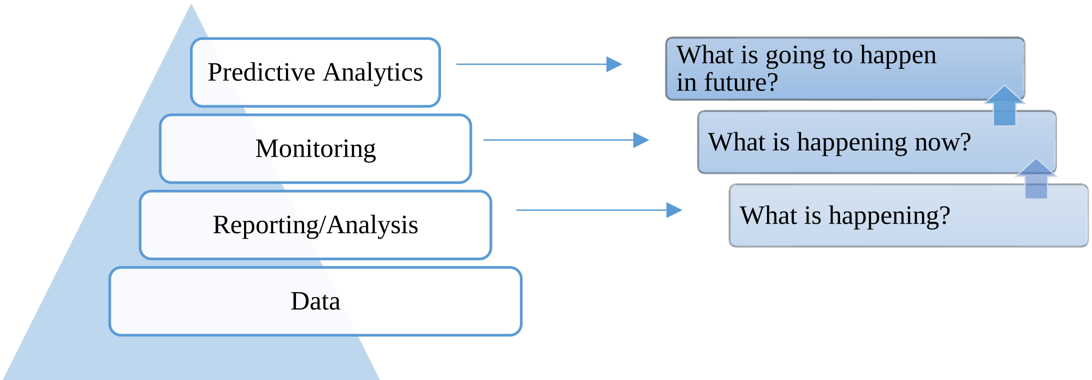

Figure 1. Predictive analytics process (Tahmine dayalı analitik süreci)

Support vector regression (SVR) is an important branch of SVM, which is one of the machine learning methods. It minimizes the optimal hyperplane searched in SVR regression and the total deviation between the sample points and the hyperplane [23]. SVR formulates an optimization problem to learn a regression function that maps from the input predictor variables to the observed output values of the response. SVR strikes a balance between model complexity and prediction error and has good performance in processing high-dimensional data [24]. Based on statistical learning theory, the method was designed to solve classification and regression problems, and then SVR was developed for prediction [25].

The GPR model is a nonparametric kernel-based probability model [26]. Gaussian processes are defined as a family of stochastic processes that provide a flexible, nonparametric tool for modeling data [27]. The expression of a nonparametric model naturally adapts to the complexity of the data. Therefore, this type of model has the advantage of being more flexible than parametric models. The Bayesian approach allows the GPR to incorporate uncertainty forecast directly into the forecast, so that a model can accept different probabilities for future probable values instead of specifying a single predicted value [28]. The GPR model is a method that is well suited for small data sets and is capable of measuring forecast uncertainty. It is suitable for solving nonlinear regression problems. GPRs are used to predict multiple target values in statistical modeling [29].

Ensemble Learning is a machine learning model that consists of a set of learners called Base Learning. The process of learning from base learners is called "meta-learning" [30]. Most ensemble methods result in a homogeneous ensemble by using a single-base learning algorithm to generate learners of the same type. There are also some methods that use multiple learning algorithms to generate heterogeneous groups [31]. Ensemble learning requires both feature selection and parameter optimization. Once the appropriate features are selected, the performance of the ensemble learning model that combines the candidate learning algorithms can be maximized through parameter optimization [32].

Regression trees methods are decision tree algorithms that examine the relationships between dependent and independent variables and summarize the results in a tree diagram [29]. There are three important elements in the tree structure: nodes represent objects, deviation paths represent the probability of attribute values, and each leaf node corresponds to the value of the entity represented by the path from the root node to the leaf node [33]. The regression trees are the inverse of the decision tree and is suitable for solving regression problems. It does not predict labels but a continuous exchange value [34]. This modeling method is a flexible technique without extensive parametric tuning. Regression trees can use different methods to calculate the node separations and determine the depth of the tree [35].

3. CASE STUDY (VAKA ÇALIŞMASI)

In this study, the problem of forecasting the number of aircraft types of an airline company is discussed. The company provides transportation services to its customers by private aircraft. The airline company charters the types of aircraft it serves from different aircraft rental companies depending on the number of passengers. For this reason, it is very important for the companys' flight planning to determine which type of aircraft to serve with for future periods based on customer demand. The company charters three different aircraft types with a capacity of 0-05, 06-10 and 10+ passengers. These aircraft types are determined by the number of passengers to be carried. For example, for a request of 12 passengers, an aircraft with a capacity of 10+ passengers must be chartered. However, if there is a request of 3 passengers, it is necessary to organise an aircraft with a capacity of 0-05 passengers. If it cannot organise an aircraft with a capacity of 0-05 passengers, it can charter aircraft with a capacity of 06-10 and 10+ passengers in order not to refuse the passenger request.

3.1. Data Set and Feature Selection (Veri Seti ve Öznitelik Seçimi)

In this study, actual data from a private airline were used to forecast aircraft type based on passenger capacity. Data on aircraft type by number of flights, number of passengers and passenger capacity between 2019 and 2021 were obtained from the airline and analyzed weekly. The forecasts in the study were made at three different points. First, the number of flights was forecast, using the data of the date and the number of flights as features. Second, the number of passengers was forecast. In forecasting the number of passengers, the data of the date, the number of flights and the number of passengers were used as features. Finally, the data of the date, number of flights, number of passengers, and aircraft type by passenger capacity are used as features for forecasting aircraft type by passenger capacity. The features used in the forecast study are shown in Figure 2.

The data set used for the study was divided into two groups: Test and Training dataset. The training data covers the years 2019-2021, while the test data covers the years 2022. After the model was trained with the training data, forecasting was made with the test data. These processes were performed in the MATLAB software environment. MATLAB statistics and the Regression Learner App in the Machine Learning Toolbox were used to forecast data using machine learning. High-performance models were selected using Regression Trees, Linear Regression, Ensemble Learning, Support Vector Regression, and Gaussian Process Regression, which are machine learning methods. In machine learning studies, many different statistical ratios (coefficient of determination, mean absolute percentage error, mean absolute error, mean square error, root mean square error, etc.) are used to evaluate the performance of the model. The coefficient of determination (R^2) provides more informative and accurate results because it has no limits of interpretability compared to other statistical ratios in determining the quality of performance [36]. The R^2 value expresses the relationship between actual values and predicted values. The R^2 value takes a value between 0-1, and the closer this value is to 1, the more accurate and sensitive the model becomes [37]. For this reason, the R^2 value was used in this study.

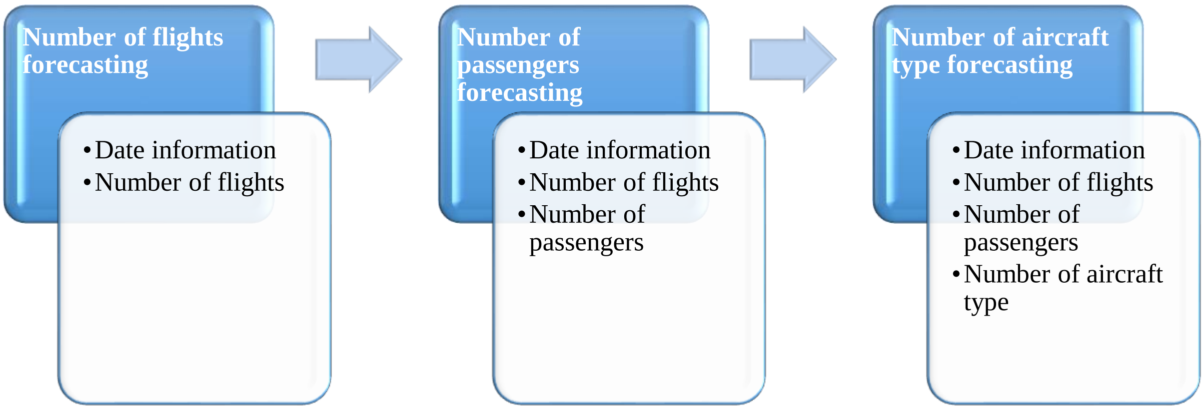

Figure 2. The areas where the forecast work is applied and the features used (Tahmin çalışmasının uygulandığı alanlar ve kullanılan özellikler)

3.2. Forecasting the Number of Flights and Passengers (Uçuş ve Yolcu Sayısının Tahmini)

In the flight count forecasting phase of the study, the model with better results was selected by training machine learning models with the dataset created, and the results of this model were used. The machine learning models used are SVM, GPR, Ensemble Learning, and Regression Trees. The attributes used for flight forecast are the week, month, year, and weekly flight number data. The flight number data were used as output parameters. The results obtained with the methods used are shown in Table 1. According to these results, the model with the best R^2 value was determined as the GPR.

Table 1. Results of the performance evaluation for flight forecasting (Uçuş tahmini için performans değerlendirmesinin sonuçları)

Methods	R^2
SVM	0.83
Ensemble Learning	0.78
GPR	0.86
Regression Trees	0.76

In the passenger number forecasting phase, the model with better results was selected by training machine learning models with the created dataset, and the results of this model were used. The machine learning models used are SVM, GPR, Ensemble Learning and Regression Trees. The attributes used for passenger forecasting are week, month, year, and the number of weekly flights and passengers. Passenger number data was used as output parameters. The results obtained with the methods used are shown in Table 2. Based on these results, the model with the best R^2 value was determined as the GPR.

Table 2. Results of the performance evaluation for passenger forecasting (Yolcu tahmini için performans değerlendirmesinin sonuçları)

Methods	R^2
SVM	0.95
Ensemble Learning	0.92
GPR	0.96
Regression Trees	0.93

3.3. Forecasting the Number of Aircraft Types by Passenger Capacity (Yolcu Kapasitesine Göre Uçak Türü Sayısının Tahmini)

In the forecast phase of the number of aircraft types according to the passenger capacity of the study, the model with better results was selected by training the machine learning models with the created dataset, and the results of this model were used. The machine learning models used are SVM, GPR, Ensemble Learning and Regression Trees. The features used to forecast the number of aircraft types according to passenger capacity were created separately for week, month, year, and number of weekly flights, number of passengers, and number of aircraft types (0-05, 06-10, 10+). This is shown in Table 4, 5, 6. The data on the number of aircraft types are used as output parameters. The results obtained with the methods used are shown in Table 3. The results show that SVM is the best model for forecasting the number of aircraft types for 0-05 and 06-10 passenger capacity, while GPR is the best model for forecasting the number of aircraft types for 10+ passenger capacity (see Figure 3, 4, 5). Machine learning involves providing a known set of input data (observations) and known responses (tags) to the data. In figure 3-5, the blue dots show the number of aircraft types used in the past years to train the model. The yellow dots represent the forecasting results of the aircraft types obtained by training the model. The red lines show the difference between the forecasted values and the actual observed values, i.e., the error. The figures show the 156-week forecast results. It observed that the demand for about 100-weekly flights is more fluctuates. The fluctuating demand observed in 2019 is due to the lack of regular customer behavior in private airline transportation. In the first half of 2020, there was a sudden decrease in demand with the occurrence of the COVID-19 pandemic. In the second half of 2020, demand for private airline transportation increased of customers who avoid public transportation. After the 100th week, there is a regularity is observed in the demand of customers for special air transportation. This is because customer behavior has changed due to the pandemic and demand has become more regular.

Table 3. Results of the performance evaluation for forecasted aircraft type (Uçak türü tahmini için performans değerlendirmesinin sonuçları)

Methods	R^2 (0-05)	R^2 (06-10)	R^2 (10+)
SVM	0.35	0.95	0.88
Ensemble Learning	0.33	0.92	0.86
GPR	0.32	0.94	0.89
Regression Trees	0.18	0.92	0.82

Table 4. Features used in the application for 0-05 passenger capacity (0-05 yolcu kapasitesi için uygulamada kullanılan öznitelikler)

Week	*Mouth*	*Year*	*Number of Flights*	*Number of Passengers*	*Number of Aircraft Types (0-05)*
1	*1*	*2019*	*56*	*249*	*1*
2	*1*	*2019*	*60*	*229*	*4*
3	*1*	*2019*	*75*	*302*	*0*
⋮	⋮	⋮	⋮	⋮	⋮
1	*1*	*2020*	*50*	*255*	*0*
2	*1*	*2020*	*80*	*296*	*0*
3	*1*	*2020*	*101*	*366*	*4*
⋮	⋮	⋮	⋮	⋮	⋮
1	*1*	*2021*	*92*	*357*	*2*
2	*1*	*2021*	*92*	*357*	*2*
3	*1*	*2021*	*91*	*356*	*2*
⋮	⋮	⋮	⋮	⋮	⋮

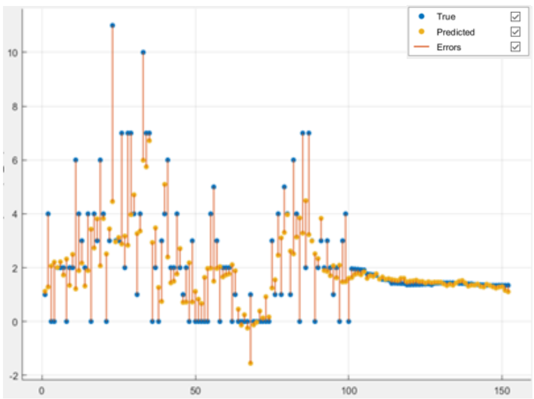

Figure 3. Best model results (0-05) (En iyi model sonuçları (0-05))

Table 5. Features used in the application for 06-10 passenger capacity (06-10 yolcu kapasitesi için uygulamada kullanılan öznitelikler)

Week	*Mouth*	*Year*	*Number of Flights*	*Number of Passengers*	*Number of Aircraft Types (06-10)*
1	*1*	*2019*	*56*	*249*	*31*
2	*1*	*2019*	*60*	*229*	*36*
3	*1*	*2019*	*75*	*302*	*45*
⋮	⋮	⋮	⋮	⋮	⋮
1	*1*	*2020*	*50*	*255*	*29*
2	*1*	*2020*	*80*	*296*	*49*
3	*1*	*2020*	*101*	*366*	*49*
⋮	⋮	⋮	⋮	⋮	⋮
1	*1*	*2021*	*92*	*357*	*54*
2	*1*	*2021*	*92*	*357*	*54*
3	*1*	*2021*	*91*	*356*	*54*
⋮	⋮	⋮	⋮	⋮	⋮

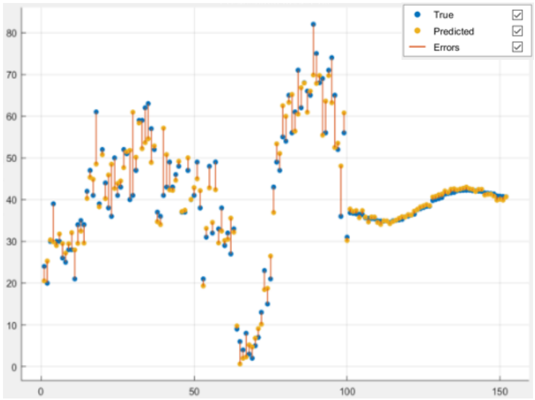

Figure 4. Best model results (06-10) (En iyi model sonuçları (06-10))

Table 6. Features used in the application for 10+ passenger capacity (10+ yolcu kapasitesi için uygulamada kullanılan öznitelikler)

Week	*Mouth*	*Year*	*Number of Flights*	*Number of Passengers*	*Number of Aircraft Types (10+)*
1	*1*	*2019*	*56*	*249*	*24*
2	*1*	*2019*	*60*	*229*	*20*
3	*1*	*2019*	*75*	*302*	*30*
⋮	⋮	⋮	⋮	⋮	⋮
1	*1*	*2020*	*50*	*255*	*21*
2	*1*	*2020*	*80*	*296*	*31*
3	*1*	*2020*	*101*	*366*	*48*
⋮	⋮	⋮	⋮	⋮	⋮
1	*1*	*2021*	*92*	*357*	*37*
2	*1*	*2021*	*92*	*357*	*37*
3	*1*	*2021*	*91*	*356*	*37*
⋮	⋮	⋮	⋮	⋮	⋮

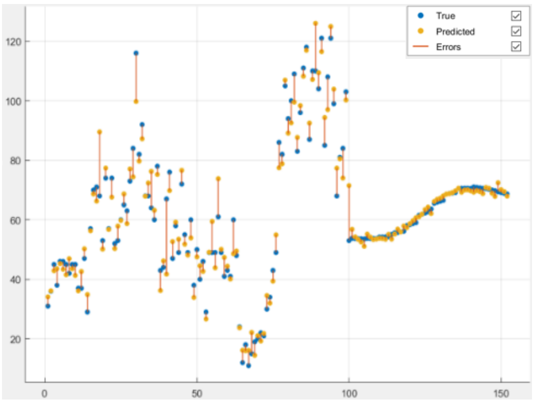

Figure 5. Best model results (10+) (En iyi model sonuçları (10+))

4. EXPERIMENTAL RESULTS (DENEYSEL BULGULAR)

This study was carried out to forecast the number of aircraft types according to the passenger capacity of an airline company for 2022. The performance evaluation was assessed using the R^2 value. For the performance of the model to be optimal, the R^2 value should be very close to 1. The study first estimated the number of weekly flights for 2022. The results show that the R^2 value is 0.86. Then, the weekly number of passengers for 2022 was predicted. Data on the number of weekly flights were added when forecasting passenger numbers. The results show that the R^2 value is 0.96. Based on the R^2 values found, it can be said that increasing the number of features is a factor that affects the accuracy of the model. Finally, the number of aircraft types was forecasted according to the passenger capacity. Given that the company leases three various types of aircraft with different capacity, it has been forecasted how many different types of aircraft should be chartered per week. For this purpose, the data of date information, the number of weekly flights, the number of weekly passengers and the weekly aircraft type are used. According to the obtained results, R^2 was 0.35 for the aircraft with capacity of 0-05 passengers, R^2 was 0.95 for the aircraft with capacity of 06-10 passengers, and R^2 was 0.89 for the aircraft with capacity of 10+ passengers. The performance evaluation of the aircraft type with a capacity of 0-

5 passengers was found to be lower than the others. Customer demand for aircraft type with a capacity of 0-5 passengers is not regular. When examination of historical data shows that this type of aircraft is used less frequently. In most of the weeks examined, there is no flight by this type of aircraft. As a result of the lack of flight data, machine learning algorithms cannot create an accurate pattern between train and test data. By increasing the number of features, the model can become more complex and the performance evaluation can be improved. Figure 6 shows that in 2022, the airline is expected to charter 105 aircraft with a capacity of 0-05 passengers, 3853 aircraft with a capacity of 06-10 passengers, and 1702 aircraft with a capacity of 10+ passengers.

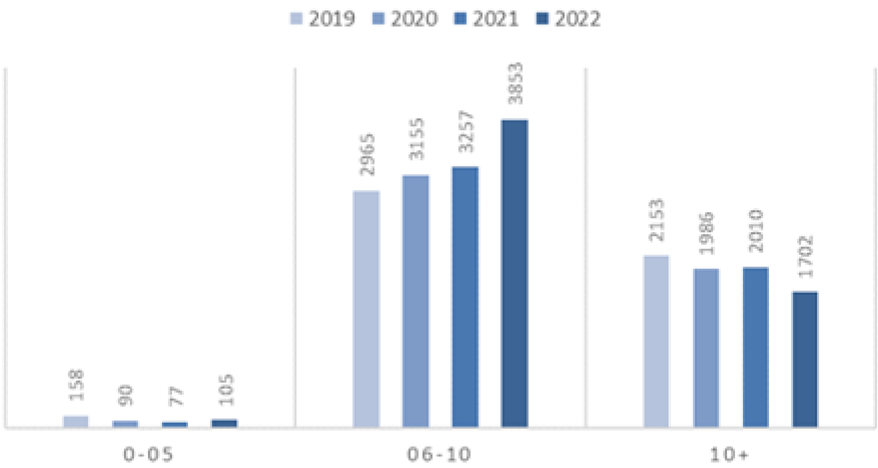

Figure 6. Forecasting results (Tahmin sonuçları)

5. DISCUSSION AND CONCLUSION
(TARTIŞMA VE SONUÇ)

With the advent of the global COVID-19 pandemic, there was a sudden decline in the number of airline passengers [38]. Travel demand has declined due to quarantine practices for high-risk countries, personal health risks, virtual platform meetings, environmental concerns, and the recession in commercial issues [39]. In 2020, the international travel market experienced significant revenue losses due to travel restrictions imposed on approximately 96% of destinations [40]. Due to the social distancing measures taken because of the COVID-19 pandemic, people's travel behavior has changed. Travel by shared transport, which increases the risk of contact with other users, has been shown to decrease [41]. During this time, when private transportation was preferred over public transportation, a transition from commercial to private aviation was evident in the U.S. aviation industry [42]. In our study, the number of aircraft types was estimated using data from a private airline company. Examination of the data reveals that the sudden declines in commercial airline transportation for 2020 and 2021 did not occur in private airline transportation. On the contrary, while 2020 shows an almost similar performance to the previous year, customer demand in 2021 increases compared to the previous two years. Due to the minimization of personal contact, the demand for private airline transportation has increased rather than the low demand for commercial passenger transportation. The forecast for 2022 projects an increase of about 7% in the number of flights compared to the pre-pandemic period.

The recession caused by the COVID-19 pandemic was felt in the commercial airline industry as well as in many other sectors. It has been observed that people prefer private means of transportation to shared transportation vehicles in order to protect themselves from the risks of the pandemic. In this study, a forecast of aircraft type chartering for 2022 according to passenger capacity was made using flight data from a private airline company for the previous three years. Data on the number of weekly flights, number of passengers, and number of aircraft types (0-05, 06-10, 10+) were used for the forecast study. Among these models, the support vector regression and Gaussian process regression models provided results with higher accuracy than other models. According to the obtained results, it is expected that airline companies can contribute to the planning of fleet type and the associated costs, personnel and other expenses.

To increase accuracy in future studies, better forecast can be made using the LSTM model, which is one of the deep learning methods. In addition, other factors that affect the number of flights can be identified and used as a feature. By comparing the forecast study made at the end of 2022 with the companys' actual data, it can be ensured that the company will get new results for 2023, which it can plan on a weekly basis. In addition, the behavior of passenger demand for private airline transportation can be modeled in the coming years as the impact of the COVID-19 pandemic gradually diminishes.

DECLARATION OF ETHICAL STANDARDS (ETİK STANDARTLARIN BEYANI)

The author of this article declares that the materials and methods they use in their work do not require ethical committee approval and/or legal-specific permission.

Bu makalenin yazarı çalışmalarında kullandıkları materyal ve yöntemlerin etik kurul izni ve/veya yasal-özel bir izin gerektirmediğini beyan ederler.

AUTHORS' CONTRIBUTIONS (YAZARLARIN KATKILARI)

Raziye KILIÇ**:** She conducted the applications, analyzed the results and performed the writing process in the article.

Uygulamaları yapmış, sonuçlarını analiz etmiş ve makalenin yazım işlemini gerçekleştirmiştir.

Özge ALBAYRAK ÜNAL**:** She conducted the applications, analyzed the results and performed the writing process in the article.

Uygulamaları yapmış, sonuçlarını analiz etmiş ve makalenin yazım işlemini gerçekleştirmiştir.

Burak ERKAYMAN**:** He conducted the process of providing the data, reviewing the results, and writing in the article.

Verilerin sağlanması, sonuçların gözden geçirilmesi ve makalenin yazılması işlemini gerçekleştirmiştir.

CONFLICT OF INTEREST (ÇIKAR ÇATIŞMASI)

There is no conflict of interest in this study.

Bu çalışmada herhangi bir çıkar çatışması yoktur.

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