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PREDICTING PUBLIC PERSONNEL SELECTION EXAMINATION ACHIEVEMENT: A DATA MINING APPROACH

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ABSTRACT

This research investigates the predictive variables related to the Public Personnel Selection Examination (KPSS), utilized for recruitment in public institutions and organizations. The study explores predictor variables' importance levels by analysing longitudinal data, including examinees' high-stakes exams, demographic information, and educational backgrounds. It compares the prediction performances of machine learning algorithms such as artificial neural networks, random forest, support vector machine, and k-nearest neighbour. The findings reveal that the quantitative test of the graduate education exam is the most influential predictor, closely followed by the mathematics test of the university entrance exam. These results highlight the importance of quantitative reasoning skills in predicting KPSS achievement. Additionally, variables related to undergraduate programs and universities demonstrate significant importance in predicting KPSS achievement. Notably, the artificial neural networks model demonstrates superior predictive accuracy compared to other models, indicating its effectiveness in KPSS prediction. This research sheds light on important predictors of KPSS achievement and provides valuable insights into the effectiveness of different prediction models.

Keywords: KPSS, artificial neural networks, support vector machine, k-nearest neighbor, random forest

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KAMU PERSONEL SEÇME SINAVI (KPSS) BAŞARISININ VERİ MADENCİLİĞİ YÖNTEMLERİYLE TAHMİN EDİLMESİ

ÖZET

Bu çalışmada kamu kurum ve kuruluşlarına işe alımlarda kullanılan Kamu Personel Seçme Sınavı (KPSS) başarısıyla ilişkili tahmin edici değişkenler araştırılmaktadır. Adayların yüksek riskli sınavları, demografik bilgileri ve eğitim geçmişlerini kapsayan boylamsal verilerin analizi yoluyla tahmin edici değişkenlerin önem düzeyleri yapay sinir ağları, rastgele orman, destek vektör makinesi ve k-en yakın komşu gibi makine öğrenme algoritmalarıyla belirlenmekte ve bu modellerin tahmin performansları karşılaştırılmaktadır. Bulgular, ALES sayısal testinin KPSS başarısının en etkili yordayıcısı olduğunu ve YGS matematik testinin de sonraki en önemli değişken olduğunu göstermektedir. Bu sonuçlar, KPSS başarısının tahmininde sayısal muhakeme becerilerinin önemini vurgulamaktadır. Ayrıca lisans programı ve üniversite değişkenleri de KPSS başarısının tahmin edilmesinde önemlidir. ANN modeli diğer modellere kıyasla üstün tahmin doğruluğu göstermekte olup KPSS tahmininde en etkili modeldir. Bu araştırma, KPSS başarısının önemli tahmin edicilerini açıklamanın yanı sıra, farklı tahmin modellerinin etkinliği hakkında önemli bilgiler de sağlamaktadır.

Anahtar Kelimeler: KPSS, yapay sinir ağları, k-en yakın komşu, destek vektör makinesi, rastgele orman

1. INTRODUCTION

Worldwide, the results of various high-stakes exams are used to recruit individuals for various government positions. In this context, exams such as the Public Service Commission exams in the United States, the Civil Service Fast Stream in the United Kingdom, the Union Public Service Commission Civil Services Examination, and the Assam Public Service Commission Exam in India, the National Civil Service Examination in China, the Central Superior Services examination in Pakistan, the Civil Service Exam in the Philippines, and the Public Personnel Selection Examination (Kamu Personeli Seçme Sınavı [KPSS]) in Türkiye are conducted for the common aim of recruitment to public institutions and organizations. These exams not only play a crucial role in shaping individuals' career paths but also have significant effects in the public sector, allowing individuals to be appointed to specific positions based on their relevant knowledge, skills, and abilities. The appointment of suitable and talented individuals for positions in the public sector profoundly impacts the productivity of civil servants and the efficiency of public services. The KPSS, one of the high-stakes exams used to make crucial decisions for individuals and society (Madaus, 1998) and applied on a large scale, is discussed within the scope of this study. The KPSS results can be utilized in various contexts, including the appointment of individuals to public institutions and organizations (Ölçme, Seçme ve Yerleştirme Merkezi [ÖSYM], 2020b), assessing the success of universities and undergraduate programs for quality determination in higher education (Yükseköğretim Kurulu [YÖK], 2023), evaluating the workforce market performance of the higher education system (UniVeri, n.d.), and identifying the average success rates of universities and undergraduate programs to assist individuals in making university choices during the higher education application process (ÖSYM, 2020d). Considering that one of the most significant factors influencing university and undergraduate program preferences is the ease of employment after graduation, universities should develop innovations that will not only meet the needs of students but also give them a competitive edge over other graduates (Özçınar, 2006). As a result, it has been observed that the achievement of KPSS is effective in the recruitment of public services and decision-making processes in education. It can also contribute to strategic planning in higher education policies to improve the quality of education.

In the literature, there is limited research on the influential factors of KPSS achievement (Bahar, 2006; Baştürk, 2008; Demir, 2015; Ercoşkun & Nalçacı, 2009; Kablan, 2010; Özçınar, 2006). In this context, Ercoşkun and Nalçacı (2009) found significant differences in KPSS scores by gender ($t = 3.430$, $p < 0.001$) and significant differences in undergraduate Grade Point Average (GPA) scores ($t = 8.142$, $p < 0.001$). Additionally, insignificant correlations were observed between KPSS and university entrance exam scores ($r = 0.052$; $p > 0.05$), while significant correlations were found between undergraduate GPA and university entrance exam scores ($r = -0.104$; $p < 0.05$), as well as undergraduate GPA and KPSS ($r = 0.371$; $p < 0.05$). Contrary to the findings of this study, Baştürk (2008) conducted a study investigating the predictive validity of KPSS for pre-service science and technology teachers, and this study revealed a statistically significant relationship between university entrance exam and KPSS scores ($r = 0.24$; $p < 0.05$), as well as between KPSS scores and undergraduate GPA ($r = 0.44$; $p < 0.05$). The study conducted by Bahar (2006) illustrated that the undergraduate GPA of teacher candidates predicts KPSS scores at different rates based on gender [male ($R^2 = 15.0$) and female ($R^2 = 14.6$)]. In Kablan's (2010) study, which investigated the relationship between undergraduate GPA and KPSS scores, it was concluded that the undergraduate GPA variable explained approximately 10% of the total variance of KPSS success and showed a significant relationship ($r = 0.315$, $p < 0.01$). Demir (2015) used Artificial Neural Networks (ANN) to predict the number of accurate responses in the KPSS Educational Sciences exam by analyzing various factors, such as high school GPA, university entrance exam scores, and midterm and final grades in undergraduate educational sciences courses of teacher candidates. The models illustrated a significant correlation between the estimated and actual number of correct answers, ranging from $r = .43$ to $r = .63$. Özçınar (2006) compared the accuracy of ANN and multiple regression models in predicting KPSS achievement based on variables such as passing grade, teaching type, and GPA from undergraduate courses related to KPSS items. The study concluded that the ANN model had more minor differences between predicted and actual scores than the regression analysis. Therefore, in light of these contradictions and limited studies explaining this phenomenon, this study questions which variables could be meaningful and valid predictors in predicting KPSS achievement.

Considering the substantial impact of the KPSS exam on individuals in terms of their employment and careers and the application of this high-stake exam in a large-scale, in-depth analysis should be conducted to obtain practical and critical findings. Upon reviewing the literature, it is evident that the studies investigating the variables predicting KPSS achievement are constrained. This study aims to contribute to this research gap by addressing these limitations and providing insights into identifying potential variables of KPSS achievement and their significance levels. The study will predict KPSS achievement by using variables such as the university entrance exam [Yükseköğretime Geçiş Sınavı (YGS)], the graduate education exam [Akademik Personel ve Lisansüstü Eğitimi Giriş Sınavı (ALES)], and the foreign language exam [Yabancı Dil Bilgisi Seviye Tespit Sınavı (YDS)] scores, high school type, high school GPA, gender, university, undergraduate program, faculty, undergraduate category, years since the degree, undergraduate GPA, and the number of taking the KPSS exam. This study will evaluate the variables affecting KPSS achievement using data mining, a knowledge discovery process from big data (Baker, 2010). Hence, the effectiveness of these methods in model evaluation performance will also be investigated. This study aims to contribute to the field of measurement and evaluation by analyzing the exams that demonstrate the success of individuals in different periods in a holistic way and determining the appropriate data mining methods used in analyzing big data in education. Since high-stakes exams are nationally administered by a single organization called the Assessment, Selection, and Placement Center (ÖSYM), the fact that different high-stakes exams' data such as YGS, KPSS, ALES, and YDS belong to the same person together makes this study significant. Therefore, within the scope of this study, the objective is to contribute to the field by collectively analyzing variables, including present and past educational achievements, other high-stakes exam results, and some educational and demographic information, from different perspectives using various data mining algorithms to assess their importance in predicting KPSS achievement.

2. METHODS

The methodology employed in this study is based on a descriptive approach in terms of evaluating numerical information and tables that vary as a result of analyses by the number of independent variables used in data mining methods and the dependent variable. Descriptive research is stated as describing a particular situation as accurately and thoroughly as possible (Büyüköztürk, Kılıç Çakmak, Akgün, Karadeniz & Demirel, 2014; Fraenkel, Wallen & Hyun, 2012).

This study followed the Cross-Industry Standard Process for Data Mining (CRISP-DM) model, developed to standardize the data mining process (Chapman et al., 2000). The CRISP-DM process model includes the steps of understanding the business, understanding the data, preparing the data, modelling, evaluating, and distributing the data (Chapman et al., 2000; Ersöz, 2019). Accordingly, the methodology of this study was formed by these steps. The analysis used the IBM SPSS Modeler program (Version 18.2) using CRISP-DM methodology (Ersöz, 2019).

In the initial phase of the CRISP-DM process, which is identified as understanding the business, the methodology of this research was determined to examine the variables influencing the examinees' KPSS achievement. This study uses data mining methods based on different algorithms to analyze these variables and compare the predictive performance of models created through analyses.

In the second stage of the CRISP-DM process, known as the data understanding phase, a dataset comprising individuals who participated in all three exams in 2020 - the KPSS, the ALES/first term, and the YDS-English exams - was utilized. This dataset was obtained anonymously from ÖSYM in adherence to ethical protocols. The dataset, characterized by its extensive nature, underwent structuring within the MS SQL Server (Version 15.0) database. Following data cleansing and transformation processes, it was prepared for data analysis. Throughout this process, variables, including gender, high school and university information, undergraduate GPA, graduation year, high school GPA, and scores from various tests, including YGS, KPSS, ALES, and YDS, were compiled.

The third stage of the CRISP-DM process is data preparation. During this phase, it was observed that the data covering exams conducted between 2012 and 2022 was shared about examinees' YGS results. For this reason, individuals with valid YGS scores were involved in the research. Additionally, regarding the university placement data, it was seen that examinees could take university entrance exams at different times and be placed in multiple higher education programs. Their first placement information was used for analysis purposes. In this dataset, it has been observed that there was a small number of examinees in some categories of university and undergraduate program features, and the number of categories in these variables is high. Considering the situation where group sizes are unequal, the results based on group means increase the explained variance rather than individual responses (Cox & Wermuth, 1992). Hence, the dataset was eliminated with the condition of having at least ten examinees (0.1%) in each category in the variables of university and undergraduate programs. As a result of the data preparation process, the dataset used in the analysis consisted of the features of 9,918 examinees.

Before the modelling stage of the CRISP-DM process, the information within the dataset underwent restructuring to facilitate analysis, and it was merged for modelling purposes, focusing on the prediction of KPSS achievement. Upon reviewing the KPSS scores data, it was observed that multiple score types correspond to different fields and subtests within the examination. Given the equal weighting of general ability and general knowledge tests, each was assigned a coefficient of 0.5 in computing the KPSSP3 score, so it was decided to employ this unified score type for all examinees. Thus, the KPSSP3 score was selected as the target variable for this study. The relationships between the independent and dependent variables were analyzed using F and t statistics through the feature selection node in IBM SPSS Modeler. Based on this analysis, 18 variables were identified as important for modelling KPSS achievement, with the high school institution type variable, including private and public groups, being excluded.

Considering other variables, the high school types variable is grouped into eleven categories. Due to less than 1% of examinees having an undergraduate graduation year of 3 and above, the years since the degree variable has been combined into a single group labelled "3+" and studied across four categories. In instances where examinees graduated from multiple undergraduate programs, data from the program they initially graduated from was included in the dataset. The undergraduate program variable was then aligned with corresponding faculties, forming faculty groups based on the examinees' undergraduate programs. Additionally, undergraduate programs were categorized into an undergraduate category based on the score type associated with each program.

Furthermore, the variable indicating university type was grouped into three categories: public, private, and foreign. The variable representing the number of examinees taking the KPSS exam from 2012 to 2020 noted that the proportion of examinees with four or more exam attempts was less than 1%, and they were grouped and analyzed as a single category. As a result of these transformations, the model dataset was obtained, and the descriptive statistics of the categorical variables in this dataset are given in Table 1.

Table 1. Descriptive Statistics of Categorical Variables in Model Data

Variables	N	%	KPSS Mean	KPSS Std. Dev.	Variables	N	%	KPSS Mean	KPSS Std. Dev.
Gender					Faculty				
Female	6415	64.68	68.84	7.02	Engineering and Architecture	2907	29.31	70.79	6.99
Male	3503	35.32	70.47	7.38	Economics And Administrative Sciences	2099	21.16	67.93	6.44
High School Type					Literature	1566	15.79	67.27	6.90
Anatolian	4895	49.35	67.10	6.10	Education	1085	10.94	69.76	6.37
General	2172	21.90	75.39	7.03	Health	1078	10.87	72.39	7.69
Anatolian Teacher	843	8.50	64.68	5.52	Science	345	3.48	65.82	5.30
Vocational	662	6.67	76.93	6.61	Law	326	3.29	77.25	6.63
Religious Vocational	501	5.05	74.76	6.64	Agriculture	147	1.48	63.90	5.06
Open Education	374	3.77	68.99	7.10	Theology	138	1.39	67.96	5.26
Science	276	2.78	66.82	6.68	Communication	111	1.12	64.09	5.04
Social Science	95	0.96	73.19	6.86	Tourism	71	0.72	61.55	3.33
Health	76	0.77	68.46	5.92	Arts and Sports	45	0.45	63.66	5.37
Military	22	0.22	70.36	6.93	Years since the Degree				
Arts and Sports	2	0.02	66.20	5.29	0	6184	62.35	68.91	6.82
University Type					1	2755	27.78	70.19	7.71
Public	8590	86.61	69.51	7.26	2	712	7.18	70.43	7.95
Private	1233	12.43	68.93	6.73	3+	267	2.69	70.34	6.68
Foreign	95	0.96	66.97	5.84	Undergraduate Category				
Number of KPSS Exam					Quantitative	4527	45.64	70.52	7.24
1	7233	72.93	68.90	6.84	Equally-Weighted	3828	38.60	69.28	7.34
2	205	2.07	71.01	8.08	Verbal	1074	10.83	66.75	5.92
3	416	4.19	69.89	7.45	Language	466	4.70	66.00	5.03
4+	219	2.21	70.40	6.62	Special Talent	23	0.23	66.47	6.46
University (Top 10 of 146)					Undergraduate Program (Top 10 of 110)				
Ankara	368	3.71	72.61	7.71	Psychology	497	5.01	71.89	7.73
Hacettepe	368	3.71	72.92	6.89	Civil Engineering	493	4.97	72.86	7.41
Gazi	364	3.67	72.22	7.33	Electrical and Electronics Engineering	455	4.59	71.39	6.88
Erciyes	329	3.32	69.07	7.44	Economy	361	3.64	67.07	6.44
İstanbul	288	2.90	70.53	6.4	International Relations	350	3.53	68.95	5.84
Anadolu	279	2.81	68.59	6.73	Architecture	330	3.33	71.79	6.60
Akdeniz	277	2.79	68.55	7.82	Business	330	3.33	66.55	6.36
Süleyman Demirel	249	2.51	67.2	7.05	Law	326	3.29	77.25	6.63
Marmara	222	2.24	70.88	6.23	Mechanical Engineering	278	2.80	69.55	6.57
Pamukkale	199	2.01	67.73	7.27	Political Science	274	2.76	70.92	6.48

As seen in Table 1, although the university variable has 146 categories, and the undergraduate program variable has 110 categories, these variables ranked according to the number of examinees in model data, and the top ten universities and undergraduate programs were illustrated.

From the perspective of numerical variables, the YGS is used for admission and placement of individuals into higher education programs and consists of four tests: Turkish, social sciences, mathematics, and science, each with 40 items (ÖSYM, 2012a, 2013a, 2014a, 2015a, 2016a, 2017a). The YGS scores of the examinees in the research sample were from various years spanning 2012 to 2017. The mean and standard deviation values presented in Table 2 are used to compute the YGS subtests' Z scores to compare them on the same scale level.

Table 2. Mean and Standard Deviation Values of YGS Tests by Years

	Turkish		Social Sciences		Mathematics		Science	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
2012	18.00	9.70	8.70	7.67	6.92	9.70	3.56	7.80
2013	16.80	9.40	12.10	8.50	7.50	9.40	3.50	7.80
2014	18.70	8.40	11.20	7.30	6.10	8.70	3.50	7.30
2015	15.80	7.50	10.70	6.80	5.20	8.10	3.90	7.30
2016	19.10	8.38	10.75	7.36	7.89	9.80	4.70	8.07
2017	17.28	8.76	12.31	7.67	5.13	7.46	4.61	7.59

(ÖSYM, 2012b, 2013b, 2014b, 2015b, 2016b, 2017b)

The ALES, on the other hand, provides scores that are used for academic staff recruitment in higher education institutions and admission to graduate education, and it consists of verbal and quantitative tests, each with 100 items to measure examinees' logical reasoning skills (ÖSYM, 2020a). In this regard, the ALES quantitative and verbal test scores were included in the model's data. The YDS is used in making important decisions such as admission to graduate programs, academic promotion, or recruitment to certain positions in public institutions and organizations, and it includes 80 items that aim to measure vocabulary, grammar, translation, and reading comprehension skills (ÖSYM, 2020c). Since the number of examinees taking the exam in foreign languages other than English is generally low, the English version of the YDS exam (YDS-English) scores was used in the study. Additionally, the grading systems for undergraduate education vary across universities, such as 4, 5, 6, 7, 10, 20, and 100. Therefore, the undergraduate GPA variable in the dataset has been standardized by converting it to a 100-point system. On the other hand, the high school GPA of examinees in the dataset has been converted into standard scores ranging from 250 to 500 points based on the secondary education graduation grades of the examinees by ÖSYM (ÖSYM, 2012a, 2013a, 2014a, 2015a, 2016a, 2017a). This variable has been directly added to the model data. As a result of the data preparation process, the numerical variables were also added to the model dataset, and their descriptive statistics are presented in Table 3.

Table 3. Descriptive Statistics of Numerical Variables in Model Data

Variables	Mean	Variance	Standard Deviation	Min.	Max.	Skewness	Kurtosis
KPSS Score (Target)	69.41	51.69	7.19	51.63	97.01	0.62	0.20
High School GPA	392.60	1833.48	42.82	250.00	500.00	-0.38	-0.32
Undergraduate GPA	74.95	108.05	10.40	30.25	100.00	-0.34	0.20
YGS Turkish Z Score	0.99	0.41	0.64	-2.22	2.93	-0.57	0.61
YGS Maths Z Score	1.14	1.24	1.11	-1.25	3.99	0.13	-0.95
YGS Social Science Z Score	0.61	1.33	1.15	-1.77	3.60	-0.22	-0.81
YGS Science Z Score	1.00	2.30	1.52	-1.34	3.99	0.39	-1.42
ALES Quantitative Test Score	23.94	215.49	14.68	-4.25	50.00	-0.02	-1.28
ALES Verbal Test Score	26.87	84.57	9.20	-4.00	50.00	-0.47	-0.11
YDS Score	38.78	416.62	20.41	1.25	100.00	0.88	-0.09

* The standard errors of Skewness for all variables are 0.025 and 0.049 for Kurtosis

Table 3 provides information about the characteristics of numerical variables, including measures of central tendency (mean), spread (variance, standard deviation), the range of values (minimum and maximum), and the shape of the distribution (skewness, kurtosis), the distribution and variability of the data were comprehensively reviewed before initiating the modelling phase. Subsequently, the prepared dataset was split into two subsets: training (70%) and test (30%) data to prevent overfitting and achieve more accurate estimations (Gholamy, Kreinovich & Kosheleva, 2018).

In the modelling phase of the CRISP-DM process, considering the data structure, features of the methods, and variable characteristics used in this study, artificial neural networks (ANN), support vector machine (SVM), k-nearest neighbor (KNN) and random forest (RF), which are widely used data mining methods providing highly accurate results in prediction (Boateng, Otoo & Abaye, 2020), were employed. Since the performance of methods can vary depending on the datasets, considering that no generalization can be made about the superiority of any method across all problem types (Boateng et al., 2020), the study investigated which method exhibited better performance in predicting the KPSS achievement by using the same training and testing datasets for each model.

ANN is a knowledge-processing system inspired by the functions of biological neural networks (Fausett, 1994). It consists of three layers: the input layer, where the data enters the network; the hidden layer, whose number and initial weight selection are crucial in processing the data; and the output layer, where target values corresponding to the input data are generated (Bramer, 2020). ANN can identify all potential interactions among variables (Mengash, 2020), exhibiting a high degree of efficiency and excellent generalization of outcomes (Musso, Cascallar, Bostani & Crawford, 2020). In this study, Multi-Layer Perceptron (MLP), which is one of the ANN models that uses backpropagation to minimize the error between the output and target values (Mitchell, 1997), was used, and the model automatically constructed one hidden layer with 16 neurons.

SVM is a method of classifying linear and non-linear data based on the hyperplane that best separates the classes (Han, Kamber & Pei, 2012). SVM can transform the non-linear data into a higher-dimensional feature space through kernel functions (Olson & Delen, 2008); the Linear Kernel function was used in this study. The regularization parameter, which is a moderator for maximizing the margin between support vectors and minimizing the error, is essential in improving the accuracy of SVM (Wendler & Gröttrup, 2021). In this regard, SVM effectively handles datasets with high dimensionality and linear non-separability and exhibits high generalization performance (Cortes & Vapnik, 1995).

KNN is a distance-based (Dunham, 2003) and efficient data mining algorithm due to its simplicity, adaptability, implementation, and capability of accurate results (Boateng et al., 2020). The appropriate value of k was selected using the cross-validation method (Larose, 2005) by taking the square root of the number of training data (Dunham, 2003). Within the analysis of the study, the value of "k" was selected as 19, which provides a minimum error rate through a 10-fold cross-validation technique. As a "d" distance criterion, Euclidean distance, which is widely used (Larose, 2005), was chosen in the study.

RF is an algorithm consisting of a group of tree-based classifiers in which each tree has the same distribution and depends on the random vector values sampled independently (Breiman, 2001). RF is one of the ensemble methods (Han et al., 2012) that demonstrates high accuracy and better generalization (Rai et al., 2021). The RF algorithm using the bootstrap technique in generating samples (Bayazit, Askar & Cosgun, 2014) was run by setting the number of trees to 10 in this study.

In the evaluation phase of CRISP-DM, the prediction performances of the models were compared with the Mean Absolute Error (MAE) and correlation coefficient (R) values. MAE, the average of the absolute values of the prediction errors, which indicate the difference between the actual and the predicted value in the model, is calculated by Equation 1 (Sammut & Webb, 2011, p.652).

$$mae = \frac{\sum_{i=1}^{n} abs(y_i - \lambda(x_i))}{n}$$

In Equation 1, n represents the number of samples in the test, y_i denotes the actual value for the test sample x_i, and $\lambda(x_i)$ indicates the predicted value for the test sample x_i. The correlation coefficient (R) measures the linear relationship between two variables, and it is calculated with Equation 2, yielding values between -1 and 1 (Han et al., 2012, p.96).

$$r_{A,B} = \frac{\sum_{i=1}^{n}(a_i - \bar{A})(b_i - \bar{B})}{n\sigma_A\sigma_B}$$

In Equation 2, n represents the sample size, and a_i and b_i are the i-th values for data sets A and B, respectively. Additionally, $\bar{A}$ and $\bar{B}$ represent the mean values of A and B, while σ_A and σ_B represent the standard deviations of A and B. Among the criteria used to examine prediction performance, models with MAE values close to zero and R values close to one are considered to have higher prediction ability (Kayri, 2015).

3. RESULTS

The study's findings, which aimed to evaluate relevant variables in predicting KPSS achievement, were discussed in two stages, including an in-depth analysis of the importance levels of predictor variables and comparisons of the data mining methods used. Firstly, the prediction performances of the KNN, SVM, ANN, and RF methods employed in this study were evaluated by comparing the models' MAE and R values, as illustrated in Figures 1 and 2.

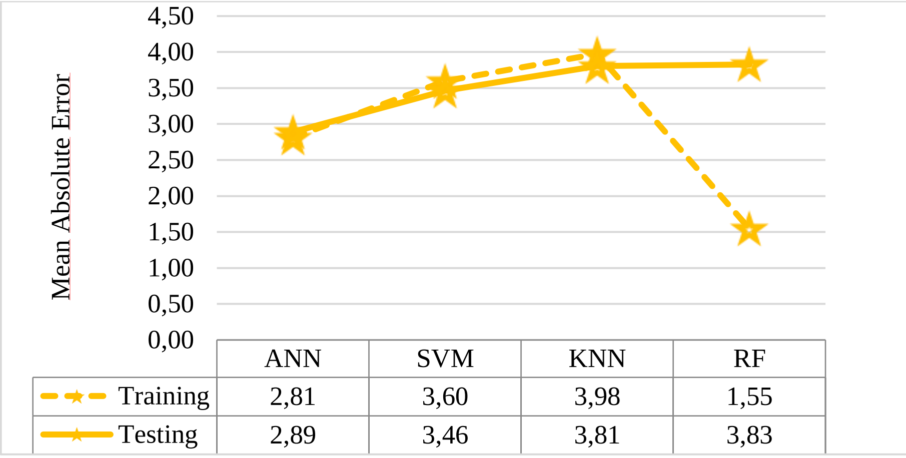

Figure 1. Mean Absolute Errors of Models

Upon examination of Figure 1, it is evident that models with lower MAE values exhibit higher performance. Among the models utilized for predicting KPSS achievement, the ANN model achieved the lowest MAE values and demonstrated the best prediction performance, with 2.81 in training and 2.89 in testing. The SVM and KNN models displayed commendable performance, with MAE values of 3.46 and 3.81, respectively. However, despite achieving the lowest error value (1.55) and displaying exceptional learning capabilities in the training data, the RF model exhibited the lowest prediction performance with the highest error value (3.83) in the testing data.

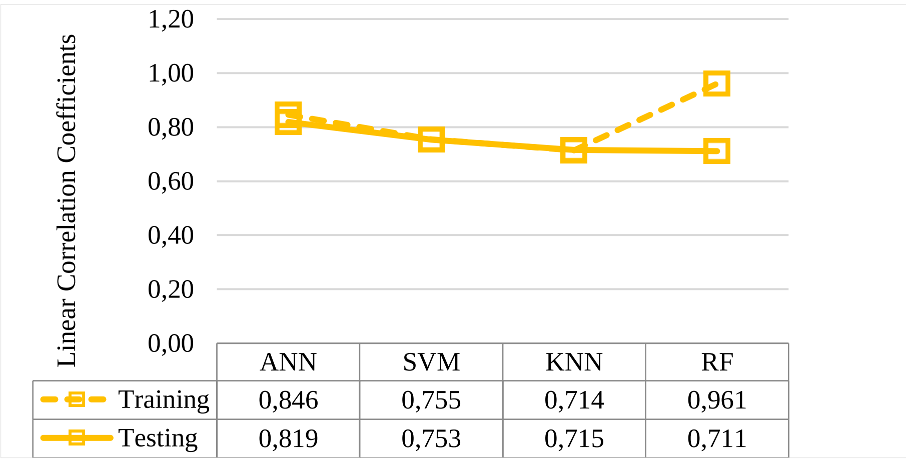

Figure 2. Linear Correlation Coefficients of Models

According to Figure 2, in evaluating the prediction performance of models, the model with a higher R between predicted and actual values tends to exhibit better performance, suggesting improved predictive accuracy. The ANN model, with the highest R-value (0.819), emerges as the most reliable predictor among the models evaluated for predicting KPSS achievement. However, the RF model exhibits an exceptionally high R-value of 0.961 in training but lower coefficients of 0.711 in testing, suggesting potential overfitting and limitations in generalization to unseen data. KNN and SVM models demonstrate moderate to high correlation coefficients, with values of 0.714 and 0.715 for KNN and 0.755 and 0.753 for SVM in training and testing, respectively. These findings reflect reasonable predictive performance and alignment with actual KPSS achievement for both models.

Therefore, evaluating prediction performance based on MAE and R reveals that the ANN model is the most accurate predictor, showcasing consistent performance across both metrics. While demonstrating exceptional accuracy in training, the RF model may require further refinement to improve generalization to unseen data. On the other hand, the KNN and SVM models exhibit moderate prediction performance with reasonable accuracy.

Secondly, the predictor importance levels were investigated by comparing models for predicting KPSS achievement. The analysis results are illustrated in Figure 3.

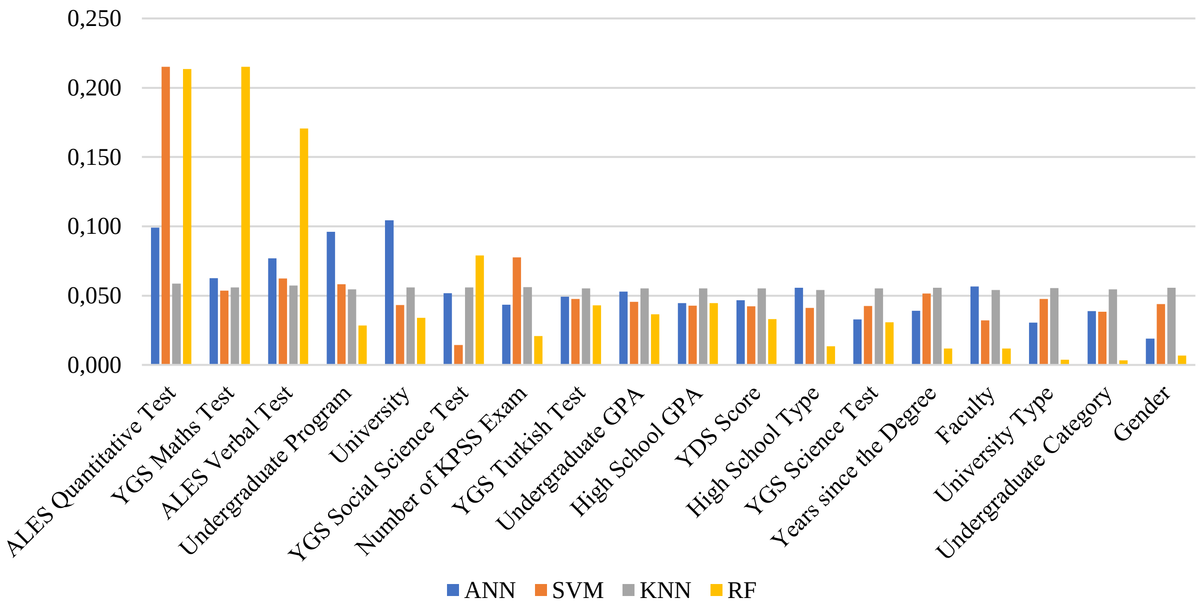

Figure 3. The Importance of Predictor Variables

When analyzing Figure 3, it is evident that although different predictor variables hold varying degrees of importance in predicting KPSS achievement, the importance levels of the variables generally exhibited similar trends across the models. Notably, variables such as the ALES quantitative test, YGS math test, and ALES verbal test appear to be consistently influential across multiple models. Upon detailed observation, it becomes apparent that the ALES quantitative test stands out as the most important predictor variable across all models, with consistently high importance scores observed in

ANN (0.099), SVM (0.215), KNN (0.059), and RF (0.213). The YGS maths test is closely behind and displays notable importance scores, particularly in RF (0.215). The ALES verbal test exhibits moderate importance across models, indicating its relevance but relatively lesser impact than the quantitative one. Undergraduate program emerges as a significant predictor in ANN with an importance score of 0.096, suggesting the potential influence of academic specialization on KPSS achievement prediction. Similarly, the university attended by examinees holds substantial importance, mainly according to ANN, with an importance score of 0.104, indicating institutional factors may play a crucial role in KPSS outcomes.

The YGS social science and YGS Turkish tests demonstrate moderate importance, albeit with slightly lower scores than the abovementioned variables. The YGS social science test demonstrates varying importance levels across models, with RF assigning the highest importance score of 0.079. The YGS Turkish test illustrates consistent importance levels across models, with ANN assigning the highest importance score of 0.049, followed closely by SVM with 0.048. The number of KPSS exams exhibits significant importance, particularly in SVM, which has an importance score of 0.078. Following these variables, undergraduate GPA and high school GPA exhibit moderate importance scores across all models, suggesting a relatively moderate or lesser impact on KPSS achievement prediction. Subsequently, the YDS score demonstrates relatively low importance, ranging from 0.033 to 0.055. On the other hand, high school type, YGS science test, years since the degree, faculty, university type, undergraduate category, and gender are among the least important variables, with importance scores generally below 0.05 across models.

4. DISCUSSION AND CONCLUSION

In conclusion, this study focused on predicting KPSS achievement, a high-stakes exam used for recruiting individuals into public institutions and organizations, by employing RF, ANN, SVM, and KNN machine learning algorithms. The importance of various predictor variables, which encompass a range of educational and demographic information across different periods, each potentially contributing to an individual's performance in the examination, was holistically investigated. This study's importance is highlighted by its ability to predict KPSS achievement by analyzing diverse longitudinal variables related to the same examinee and its capacity to rank these variables according to their significance levels. The study also provides valuable insights into the relevant variables and the performance of various prediction algorithms by comparing predictive models for KPSS achievement.

The study's results indicate that the analysis of the predictive variables reveals that the ALES quantitative test score consistently emerged as the most influential predictor across all models, followed closely by the YGS mathematics test score. These findings underscore the significance of quantitative reasoning skills in predicting KPSS achievement. This result also suggests that ALES and YGS exams have high predictive validity for KPSS. Notably, the situation where the performance in other high-stakes exams emerges as the variables with relatively highest importance in predicting examinees' KPSS achievement supports the consistency of exam outcomes. These findings provide further evidence of the reliability of high-stakes exams regarding consistency.

The analysis of longitudinal real data, covering the period from the YGS taken at university entrance to the KPSS taken at university graduation within university education, reveals that the YGS mathematics test scores are a significant predictor of KPSS achievement. In parallel with this result, Arıkan and D'Costa (2016) arrived at a comparable finding, suggesting that abilities obtained upon high school graduation could forecast proficiency levels upon university graduation. Similarly, Bahar (2011) and Baştürk (2008) identified a statistically significant relationship demonstrating predictive validity in predicting KPSS scores based on university entrance exam results. Thus, it can be inferred that individuals' achievement statuses exhibit a comprehensive structure, and this study offers insights into the longitudinal inference.

Additionally, undergraduate program and university variables demonstrate notable importance, indicating the potential influence of academic specialization and institutional factors on KPSS scores. Safran, Kan, Üstündağ, Birbudak, and Yıldırım (2014), in their study investigating the KPSS success of the examinees according to their undergraduate program, concluded that the average success scores of teacher candidates who graduated from the faculty of education were statistically significantly higher. Furthermore, the findings suggesting significant disparities in KPSS achievements based on undergraduate programs (Özkan & Pektaş, 2011; Yeşil, Korkmaz & Kaya, 2009) corroborate the outcomes of this research. The findings of this study support previous research illustrating a significant relationship between undergraduate GPA and KPSS performance (Açıl, 2010; Bahar, 2011; Baştürk, 2008; Ercoşkun & Nalçacı, 2009; Kablan, 2010; Yeşil, Korkmaz & Kaya, 2009), indicating a moderate effect size in prediction. This finding is in line with the results of Kösterelioğlu, Kösterelioğlu and Kilmen (2008).

Conversely, the consistently low significance values of variables such as high school type, university type, faculty, undergraduate category, years since graduation, and gender in predicting KPSS achievement across all models suggest indicators of the fairness, equity, and inclusivity of the KPSS. This finding is also supported by the study of Şen, Uçar, and Delen (2012), wherein they concluded that the gender variable is not as important as other characteristics as a result of the model developed for the prediction of secondary education placement test scores.

Further examination of model performance emphasizes that ANN outperforms other models and offers the most accurate and consistent predictions of KPSS achievement. Likewise, in studies aimed at predicting success, the ANN model had better prediction performance (Bahadır, 2013; Çırak, 2012; Demir, 2015; Jidagam & Rizk, 2016; Özçınar, 2006; Şengür & Tekin, 2013). In contrast, although the RF model achieves low error and high correlation coefficient values in training, its performance in testing data suggests potential overfitting and limitations in generalization. Therefore, while the RF model may require refinement to enhance generalization, the KNN and SVM models demonstrate moderate prediction performance with reasonable accuracy.

The contributions of this research are thoroughly investigating the variables related to KPSS achievement by using longitudinal and real-world datasets. Furthermore, considering the study's practical implications, it could offer valuable insights into long-term predictors of KPSS performance, thereby informing the development of targeted strategies for examinee support and preparation. Meanwhile, this research can guide decision-making processes in selecting the most suitable model for predicting KPSS achievement.

Further research could explore additional predictor variables such as socio-economic background, study habits, and psychological factors to offer deeper insights into examinees' performance. Investigating interaction effects between predictors and examining non-linear relationships could provide a more comprehensive understanding of the variables influencing KPSS achievement. Additionally, exploring the applicability of emerging machine learning algorithms, such as deep learning and gradient boosting, may also enhance prediction accuracy.

REFERENCES

Açıl, Ü. (2010). Ö*ğretmen adaylarının akademik başarıları ile KPSS puanları arasındaki ilişkinin çeşitli değişkenler açısından incelenmesi* (Publication No. 264743) [Master's thesis, Mustafa Kemal University]. YOK Thesis Center.

Arıkan, S., & D'Costa, A. (2016). ÖSS ve LES ile ölçülen sayısal ve sözel beceriler arasındaki ilişki. *Mersin Üniversitesi Eğitim Fakültesi Dergisi, 12*(1), 303-313. https://doi.org/10.17860/efd.71302

Bahadır, E. (2013). *Yapay Sinir Ağları ve Lojistik Regresyon Analizi Yaklaşımları ile Öğretmen Adaylarının Akademik Başarılarının Tahmini,* (Publication No. 349939) [Doctoral thesis, Marmara University]. YOK Thesis Center.

Bahar, H.H., (2006). KPSS puanlarının akademik başarı ve cinsiyet açısından değerlendirilmesi. *Eğitim ve Bilim*, *31*(140), 68-74. https://egitimvebilim.ted.org.tr/index.php/EB/article/view/5010

Bahar, H.H., (2011). ÖSS puanı ve lisans mezuniyet notunun KPSS 10 Puanını Yordama Gücü. *Eğitim ve Bilim*, *36*(162), 168-181. https://egitimvebilim.ted.org.tr/index.php/EB/article/view/801

Baker, R.S.J.d. (2010). Data mining. In P. Peterson, E. Baker & B. McGaw (Eds.), *International Encyclopedia of Education* (3rd ed., pp. 112-118). Elsevier. https://doi.org/10.1016/B978-0-08-044894-7.01318-X.

Baştürk, R. (2008). Fen ve teknoloji alanı öğretmen adaylarının kamu personeli seçme sınavı başarılarının yordanması. *İlköğretim Online, 7* (2), 323-332. https://dergipark.org.tr/tr/pub/ilkonline/issue/8601/107111

Bayazit, A., Askar, P., & Cosgun, E. (2014). Predicting learner answers correctness through eye movements with random forest. In A. Peña-Ayala (Ed.), *Educational data mining* (pp.203-226). Springer. https://link.springer.com/book/10.1007/978-3-319-02738-8

Boateng, E.Y., Otoo, J. and Abaye, D.A. (2020) Basic tenets of classification algorithms K-nearest-neighbor, support vector machine, random forest and neural network: A review. *Journal of Data Analysis and Information Processing*, 8, 341–357. https://doi.org/10.4236/jdaip.2020.84020

Bramer, M. (2020). *Principles of data mining* (4th ed.). London: Springer.

Breiman, L. (2001). Random forests, *Machine Learning*, *45*(1) 5–32. https://doi.org/10.1023/A:1010933404324

Büyüköztürk, Ş., Kılıç Çakmak, E., Akgün, Ö.E., Karadeniz, Ş. & Demirel, F. (2014). *Bilimsel araştırma yöntemleri* (18th ed.). Ankara: Pegem Akademi.

Chapman, P., Clinton, J., Kerber, R., Khabaza, T., Reinartz, T., Shearer, C. & Wirth, R. (2000). *CRISP-DM 1.0 step-by-step data mining guide*. SPSS inc. URL: https://www.kde.cs.uni-kassel.de/wp-content/uploads/lehre/ws2012-13/kdd/files/CRISPWP-0800.pdf

Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning*, 20, 273-297. http://dx.doi.org/10.1007/BF00994018

Cox, D. R., & Wermuth, N. (1992). A comment on the coefficient of determination for binary responses. *The American Statistician*, 46(1), 1–4. https://doi.org/10.2307/2684400

Çırak, G. (2012). *Yükseköğretimde öğrenci başarılarının sınıflandırılmasında yapay sinir ağları ve lojistik regresyon yöntemlerinin kullanılması* (Publication No. 311755) [Master's thesis, Ankara University]. YOK Thesis Center.

Demir, M. (2015). Predicting pre-service classroom teachers' civil servant recruitment examination's educational sciences test scores using artificial neural networks. *Educational Sciences: Theory & Practice, 15*(5), 1169–1177. https://doi.org/10.12738/estp.2015.5.0018

Dunham, M.H. (2003). *Data mining: Introductory and advanced topics*. New Jersey: Pearson Education.

Ercoşkun, M. H., & Nalçacı, A. (2009). Sınıf öğretmeni adaylarının ÖSS, akademik ve KPSS başarılarının çeşitli değişkenler açısından incelenmesi. *Kastamonu Eğitim Dergisi, 17*(2), 479–486.

Ersöz, F. (2019). *Veri madenciliği teknikleri ve uygulamaları.* Ankara: Seçkin Yayıncılık.

Fausett, L. (1994). *Fundamentals of neural networks: architectures, algorithms, and applications.* New Jersey: Prentice-Hall Englewood Cliffs.

Fraenkel, J.R., Wallen, N.E., & Hyun, H.H. (2012). *How to design and evaluate research in education* (8th ed.). New York: McGraw-Hill.

Gholamy, A., Kreinovich, V., & Kosheleva, O. (2018). Why 70/30 or 80/20 relation between training and testing sets: A pedagogical explanation. *Departmental Technical Reports (CS)*. 1209. https://scholarworks.utep.edu/cs_techrep/1209

Jidagam, R., & Rizk, N. J. (2016). *Evaluation of predictive data mining algorithms in student academic performance.* Paper presented at the meeting of 10th International Technology, Education and Development Conference, Valencia, Spain. Retrieved from https://doi.org/10.21125/inted.2016.0487

Han, J., Kamber, M., & Pei, J. (2012). *Data mining: concepts and techniques* (3rd ed.). Waltham: Morgan Kaufmann.

Kablan, (2010). Akademik mezuniyet ortalama puanı ile KPSS başarı puanı arasındaki ilişki. *Uludağ Üniversitesi Eğitim Fakültesi Dergisi, 23* (2), 451-470. https://dergipark.org.tr/tr/download/article-file/153416

Kayri, M. (2015). An intelligent approach to educational data: Performance comparison of the multilayer perceptron and the radial basis function artificial neural networks. *Educational Sciences: Theory & Practice, 15*(5), 1247–1255. https://doi.org/10.12738/estp.2015.5.0238

Kösterelioğlu, İ., Kösterelioğlu, M.A., & Kilmen, S. (2008). Kamu personeli seçme sınavı puanları ile lisans diploma notu arasındaki ilişkilerin çeşitli değişkenlere göre incelenmesi. *Abant İzzet*

Baysal Üniversitesi Eğitim Fakültesi Dergisi, 8(1), 151-160. https://dergipark.org.tr/tr/download/article-file/16612

Larose, D. T. (2005). *Discovering knowledge in data: An introduction to data mining*. New Jersey: John Wiley & Sons.

Madaus, G. (1998). The distortion of teaching and testing: High-stakes testing and instruction. *Peabody Journal of Education*, *65*(3), 29–46. https://www.jstor.org/stable/1492818

Mengash, H.A. (2020). Using data mining techniques to predict student performance to support decision-making in university admission systems. *IEEE Access*, 8, 55462-55470. https://ieeexplore.ieee.org/document/9042216

Mitchell, T.M. (1997). *Machine learning*. New York: McGraw-Hill.

Musso, M. F., Cascallar, E. C., Bostani, N., & Crawford, M. (2020). Identifying reliable predictors of educational outcomes through machine-learning predictive modeling. *In Frontiers in Education*, *5*, 104. https://doi.org/10.3389/feduc.2020.00104

Olson, D.L., & Delen, D. (2008). *Advanced data mining techniques*. Berlin: Springer.

Ölçme, Seçme ve Yerleştirme Merkezi (ÖSYM). (2012a). *2012 Öğrenci Seçme ve Yerleştirme Sistemi (ÖSYS) Kılavuzu.* ÖSYM. Retrieved May 22, 2023, from https://www.osym.gov.tr/Eklenti/173,klavuz-2012mail-kpdf.pdf?0

Ölçme, Seçme ve Yerleştirme Merkezi (ÖSYM). (2012b). *YGS Sonuçlarına İlişkin Sayısal Bilgiler*. ÖSYM. Retrieved May 22, 2023, from https://www.osym.gov.tr/TR,986/2012-ygs-sonuclarina-iliskin-sayisal-bilgiler.html

Ölçme, Seçme ve Yerleştirme Merkezi (ÖSYM). (2013a). *2013 Öğrenci Seçme ve Yerleştirme Sistemi (ÖSYS) Kılavuzu.* ÖSYM. Retrieved May 22, 2023, from https://dokuman.osym.gov.tr/pdfdokuman/2013/OSYS/2013OSYSSISTEMKILAVUZU%2021%2003%202013.pdf

Ölçme, Seçme ve Yerleştirme Merkezi (ÖSYM). (2013b). *Yükseköğretime Geçiş Sınavının Değerlendirilmesi.* ÖSYM. Retrieved May 22, 2023, from https://www.osym.gov.tr/TR,896/2013-yuksekogretime-gecis-sinavinin-2013-ygs-degerlendirilmesi-01042013.html

Ölçme, Seçme ve Yerleştirme Merkezi (ÖSYM). (2014a). *2014 Öğrenci Seçme ve Yerleştirme Sistemi (ÖSYS) Kılavuzu.* ÖSYM. Retrieved May 22, 2023, from https://dokuman.osym.gov.tr/pdfdokuman/2014/YGS/2014_OSYS_KILAVUZU_02_01_2014.pdf

Ölçme, Seçme ve Yerleştirme Merkezi (ÖSYM). (2014b). *Yükseköğretime Geçiş Sınavının Değerlendirilmesi*. ÖSYM. Retrieved May 22, 2023, from https://www.osym.gov.tr/TR,829/2014-yuksekogretime-gecis-sinavinin-2014-ygs-degerlendirilmesi-29032014.html

Ölçme, Seçme ve Yerleştirme Merkezi (ÖSYM). (2015a). *2015 Öğrenci Seçme ve Yerleştirme Sistemi (ÖSYS) Kılavuzu.* ÖSYM. Retrieved May 22, 2023, from https://dokuman.osym.gov.tr/pdfdokuman/2015/YGS/2015_OSYS_KILAVUZ.pdf

Ölçme, Seçme ve Yerleştirme Merkezi (ÖSYM). (2015b). *YGS Sonuçlarına İlişkin Sayısal Bilgiler*. ÖSYM. Retrieved May 22, 2023, from https://www.osym.gov.tr/TR,58/2015-ygs-sonuclarina-iliskin-sayisal-bilgiler.html

Ölçme, Seçme ve Yerleştirme Merkezi (ÖSYM). (2016a). *2016 Öğrenci Seçme ve Yerleştirme Sistemi (ÖSYS) Kılavuzu.* ÖSYM. Retrieved May 22, 2023, from https://dokuman.osym.gov.tr/pdfdokuman/2016/YGS/2016-OSYSKILAVUZU11012016.pdf

Ölçme, Seçme ve Yerleştirme Merkezi (ÖSYM). (2016b). *YGS Sonuçlarına İlişkin Sayısal Bilgiler.* ÖSYM. Retrieved May 22, 2023, from http://dokuman.osym.gov.tr/pdfdokuman/2016/YGS/2016_YGS_Sayisal_Bilgiler.pdf

Ölçme, Seçme ve Yerleştirme Merkezi (ÖSYM). (2017a). 2017 *Öğrenci Seçme ve Yerleştirme Sistemi (ÖSYS) Kılavuzu*. ÖSYM. Retrieved May 22, 2023, from https://dokuman.osym.gov.tr/pdfdokuman/2017/OSYS/KILAVUZ18042017.pdf

Ölçme, Seçme ve Yerleştirme Merkezi (ÖSYM). (2017b). *YGS Sonuçlarına İlişkin Sayısal Bilgiler.* ÖSYM. Retrieved May 22, 2023, from https://www.osym.gov.tr/TR,13047/2017-ygs-sinav-sonuclarina-iliskin-sayisal-bilgiler.html

Ölçme, Seçme ve Yerleştirme Merkezi (ÖSYM). (2020a). *Akademik Personel ve Lisansüstü Eğitimi Giriş Sınavı (ALES) İlkbahar Dönemi Kılavuzu.* ÖSYM. Retrieved June 14, 2023, from https://dokuman.osym.gov.tr/pdfdokuman/2020/ALES-1/aleskilavuz15052020.pdf

Ölçme, Seçme ve Yerleştirme Merkezi (ÖSYM). (2020b). *2020 Kamu Personel Seçme Sınavı (Kpss) Kılavuzu Lisans.* ÖSYM. Retrieved July 12, 2023, from https://dokuman.osym.gov.tr/pdfdokuman/2020/KPSS/kilavuz02022021.pdf

Ölçme, Seçme ve Yerleştirme Merkezi (ÖSYM), (2020c). *2020 Yabancı Dil Bilgisi Seviye Tespit Sınavı (YDS) Kılavuzu.* ÖSYM. Retrieved June 15, 2023, from https://dokuman.osym.gov.tr/pdfdokuman/2020/YDS-1/kilavuz18082020.pdf

Ölçme, Seçme ve Yerleştirme Merkezi (ÖSYM). (2020d). *2020 Yükseköğretim Kurumları Sınavı (YKS) Yükseköğretim Programları ve Kontenjanları Kılavuzu*. ÖSYM. Retrieved June 10, 2023, from https://dokuman.osym.gov.tr/pdfdokuman/2020/YKS/tkilavuz13082020.pdf

Özçınar, H. (2006). *KPSS sonuçlarının veri madenciliği yöntemleriyle tahmin edilmesi* (Publication No. 180572) [Master's thesis, Pamukkale University]. YOK Thesis Center.

Özkan, R., & Pektaş. S. (2011). Eğitim fakültesi son sınıf öğrencilerinin mezuniyet başarı notları ile KPSS puanları arasındaki ilişki üzerine bir araştırma (eğitim fakültesi örneği). *Türklük Bilimi Araştırmaları, 30*, 269-281. https://dergipark.org.tr/tr/download/article-file/157093

Rai, S., Shastry, K.A., Pratap, S., Kishore, S., Mishra, P., Sanjay, H.A. (2021). Machine learning approach for student academic performance prediction. In: Bhateja, V., Peng, SL., Satapathy, S.C., Zhang, YD. (eds) *Evolution in Computational Intelligence. Advances in Intelligent Systems and Computing, 1176*. Springer. https://doi.org/10.1007/978-981-15-5788-0_58

Safran, M., Kan, A., Üstündağ, M.T., Birbudak, T.S., & Yıldırım, O. (2014). 2013 KPSS sonuçlarının öğretmen adaylarının mezun oldukları alanlara göre incelenmesi. *Eğitim ve Bilim, 39*(171), 13-25. https://egitimvebilim.ted.org.tr/index.php/EB/article/view/3044

Sammut, C., & Webb, G.I. (Ed.). (2011). *Encyclopedia of Machine Learning*. New York: Springer.

Şen, B., Uçar, E., & Delen, D. (2012). Predicting and analyzing secondary education placement-test scores: A data mining approach. *Expert Systems with Applications, 39*(10), 9468-9476. https://doi.org/10.1016/j.eswa.2012.02.112

Şengür, D., & Tekin, A. (2013). Öğrencilerin mezuniyet notlarının veri madenciliği metotları ile tahmini. *Bilişim Teknolojileri Dergisi*, *6*(3), 7-16. https://dergipark.org.tr/tr/pub/gazibtd/issue/6629/88010

UniVeri. (n.d.). *Türkiye Cumhuriyeti Cumhurbaşkanlığı İnsan Kaynakları Ofisi UniVeri*. Retrieved February 29, 2024, from https://www.cbiko.gov.tr/projeler/uni-veri

Wendler, T., & Gröttrup, S. (2021). *Data mining with SPSS Modeler theory, exercises and solutions* (2nd ed.). Springer. https://doi.org/10.1007/978-3-030-54338-9

Yeşil, R., Korkmaz, Ö., & Kaya, S. (2009). Eğitim fakültesindeki akademik başarının kamu personeli seçme sınavındaki başarı üzerinde etkisi. *Fırat Üniversitesi Sosyal Bilimler Dergisi, 19*(2), 149-160. https://dergipark.org.tr/tr/download/article-file/72001

Yükseköğretim Kurulu (YÖK), 2023. *Üniversite izleme ve değerlendirme genel raporu 2023*. Retrieved February 13, 2024, from https://www.yok.gov.tr/Documents/Yayinlar/2023-universite-izleme-ve-degerlendirme-genel-raporu.pdf

GENİŞLETİLMİŞ TÜRKÇE ÖZET

KAMU PERSONEL SEÇME SINAVI (KPSS) BAŞARISININ VERİ MADENCİLİĞİ YÖNTEMLERİYLE TAHMİN EDİLMESİ

GİRİŞ

Kamu personel alımlarında kritik bir rol oynayan ve ulusal düzeyde geniş ölçekte uygulanan KPSS gibi yüksek riskli sınavların sonuçları, bireylerin kariyer yolculuklarını şekillendirmenin yanı sıra kamuda belirli pozisyonlara bireylerin gerekli bilgi, beceri ve yetenekleri doğrultusunda görevlendirilebilmelerine olanak tanımasıyla kamusal alanda da önemli etkilere sahiptir. Bu nedenle, sınav sonuçları kamu hizmetlerinin verimliliği ve etkinliği üzerinde derin bir etkiye sahiptir. KPSS kamu hizmetlerinde işe alım ve eğitimde karar verme süreçlerinde etkili olup sonuçları eğitimin kalitesinde iyileştirmelere yönelik yükseköğretim politikalarında stratejik planlamalar yapılmasına katkı sağlamaktadır. Literatürde KPSS başarısının araştırıldığı çalışmaların sınırlı olduğu gözlenmiş olup araştırma kapsamında KPSS başarısının tahminindeki yordayıcı değişkenleri incelemek amaçlanmıştır. Çalışma kapsamında bireyin sınavdaki performansına katkıda bulunabilecek farklı dönemlerdeki eğitimsel ve demografik bilgilerini kapsayan çeşitli yordayıcı değişkenlerin önemi bütünsel olarak araştırılmıştır. Bu çalışmanın önemi aynı bireye ait boylamsal anlamda çeşitli değişkenlere bağlı KPSS başarısını tahmin etmesi ve bu değişkenleri önem düzeylerine göre derecelendirme imkânı sunmasıdır.

YÖNTEM

Araştırmanın metodolojisi, veri madenciliği yöntemlerinde kullanılan bağımsız değişken sayısına ve bağımlı değişkenin türüne göre analizler sonucu farklılık gösteren sayısal bilgi ve tabloların değerlendirilmesi açısından betimsel bir yaklaşıma dayanmaktadır. Bu çalışmada, veri madenciliği sürecini standartlaştırmak için geliştirilen işi anlama, veriyi anlama, veri hazırlama, modelleme, değerlendirme ve dağıtma adımlarını içeren CRISP-DM süreç modeli takip edilmiş ve IBM SPSS Modeler 18.2 programı kullanılmıştır.

Çalışma verisi 2020 yılında KPSS Lisans, ALES/1. Dönem ve YDS-İngilizce sınavlarından üçüne de giren 9.918 adayın YGS, ALES, YDS puanları, lise türü, ortaöğretim başarı puanı (OBP), cinsiyet, üniversite, lisans programı, fakülte, lisans alanı, lisans mezuniyetinden sonra geçen yıl, akademik not ortalaması (ANO) ve KPSS sınavına girme sayısı bilgilerinden oluşmaktadır. Araştırmadaki veri yapısı, değişken karakteristikleri ve yöntemlerin özellikleri göz önünde bulundurulduğunda, KPSS başarısını tahmin etmede kullanılabilecek potansiyel değişkenlerin önem düzeylerini belirlemek amacıyla yapay sinir ağları (ANN), rastgele orman (RF), k-en yakın komşu (KNN) ve destek vektör makinesi (SVM) veri madenciliği yöntemleri kullanılmıştır. Çalışmada kullanılan yöntemlerinin tahmin performansları, modellerin ortalama mutlak hata (MAE) ve lineer korelasyon katsayısı (R) değerleri karşılaştırılarak değerlendirilmiştir.

TARTIŞMA, SONUÇ ve ÖNERİLER

Sonuç olarak, araştırma kapsamında KPSS başarısına ilişkin değişkenler boylamsal ve gerçek veri seti kullanılarak çeşitli makine öğrenimi modelleriyle derinlemesine incelenip modellerin tahmin performansları değerlendirilmiştir. KPSS başarısının tahmininde yordayıcı değişkenler farklı önem değerlerine sahip olmasına rağmen, değişkenlerin önem düzeyleri genel olarak modeller arasında benzer eğilimler göstermiştir. ALES sayısal testi tüm modeller arasında tutarlı bir şekilde en etkili yordayıcı ve YGS matematik testi de hemen sonraki en önemli değişkendir. Bu bulgular, KPSS başarısının tahmininde sayısal muhakeme becerilerinin önemini vurgulamaktadır. Aynı zamanda bulgular, ALES ve YGS sınavlarının KPSS başarısını yordama geçerliliğinin yüksek olduğunu göstermektedir. Bireylerin KPSS başarısının tahmininde önem değeri görece en yüksek olan değişkenlerin diğer yüksek riskli sınavlardaki başarı durumları olması durumu sınavların tutarlı sonuçlar sunduğunu desteklemektedir. Sonuç olarak, bu durum yüksek riskli sınavların tutarlılık anlamındaki güvenirliğine de kanıt sunmaktadır.

Üniversiteye giriş amacıyla uygulanan YGS'den üniversite mezuniyet aşamasında girilen KPSS'ye kadar olan üniversite eğitimi sürecini kapsayan zaman dilimi göz önünde bulundurulduğunda boylamsal anlamda süreci kapsayan gerçek verinin analizinde YGS matematik test puanları KPSS başarısının önemli bir yordayıcısı olarak belirlenmiştir. Bu sonuca paralel olarak Arıkan ve D'Costa (2016) da çalışmalarında lise mezuniyeti sonunda kazanılan becerilerin üniversite mezuniyetindeki yeterlilik düzeylerini tahmin edilebileceği sonucuna ulaşmıştır. Benzer şekilde Bahar (2011) ve Baştürk (2008) üniversite giriş sınavı ile KPSS puanlarının yordama geçerliğinde istatistiksel olarak anlamlı bir ilişki tespit etmişlerdir. Buna göre, bireylerin başarı durumlarının bütüncül bir yapı gösterdiği ve bu çalışmanın boylamsal anlamda çıkarım imkânı sağladığı sonucuna varılabilir.

Ayrıca lisans programı ve üniversite değişkenleri de önem değeri yüksek yordayıcılardır, bu durum akademik uzmanlaşma ve kurumsal faktörlerin KPSS puanları üzerindeki potansiyel etkisini göstermektedir. Safran, Kan, Üstündağ, Birbudak ve Yıldırım (2014), sınava girenlerin lisans programlarına göre KPSS başarılarını araştırdıkları çalışmada, eğitim fakültesi mezunu öğretmen adaylarının ortalama başarı puanlarının istatistiksel olarak anlamlı düzeyde daha yüksek olduğu sonucuna varmışlardır. Ayrıca lisans programlarına göre KPSS başarılarında anlamlı farklılıklar olduğunu gösteren bulgular (Özkan ve Pektaş, 2011; Yeşil, Korkmaz ve Kaya, 2009) bu araştırmanın sonuçlarını desteklemektedir. Bu çalışmanın bulguları, ANO ile KPSS performansı arasında anlamlı bir ilişki olduğunu gösteren çalışma sonuçlarını (Açıl, 2010; Bahar, 2011; Baştürk, 2008; Ercoşkun & Nalçacı, 2009; Kablan, 2010; Yeşil, Korkmaz & Kaya, 2009) desteklemekle birlikte bu değişkenin KPSS başarısının tahmininde orta düzeyde bir etkisi olduğu sonucuna ulaşılmıştır. Bu bulgu Kösterelioğlu, Kösterelioğlu ve Kilmen (2008) tarafından yapılan çalışmanın sonuçlarıyla tutarlılık göstermektedir.

Araştırma sonuçlarında lise türü, üniversite türü, fakülte, lisans alanı, lisans mezuniyetinden sonra geçen yıl ve cinsiyet gibi değişkenlerin KPSS başarısını tahmin eden modellerde genel olarak önem değerlerinin düşük olması, KPSS'nin tarafsızlığı, eşitliği ve kapsayıcılığına dair gösterge sunmaktadır. Bu bulgu Şen, Uçar ve Delen'in (2012) ortaöğretime yerleştirme testi puanlarının tahminine yönelik geliştirilen model sonucunda cinsiyet değişkenin diğer özellikler kadar önemli olmadığı sonucuna ulaştıkları çalışmayla da desteklenmektedir. Cinsiyet gibi değişkenlerin minimal etkisi, sınavın objektif bir ölçüt olduğuna ve yansızlığına işaret etmektedir.

Modellerin performansları karşılaştırıldığında, ANN en düşük MAE ve en yüksek R değeriyle en iyi tahmin performansı gösteren, KPSS başarısına ilişkin en doğru ve tutarlı tahminleri sunan modeldir. Benzer şekilde başarıyı yordamaya yönelik yapılan çalışmalarda da ANN modelinin tahmin performansının daha iyi olduğu görülmüştür (Bahadır, 2013; Çırak, 2012; Demir, 2015; Jidagam ve Rizk, 2016; Özçınar, 2006; Şengür ve Tekin, 2013). Buna karşılık, RF modeli eğitimde düşük hata ve yüksek korelasyon katsayısı değerleri elde etmesine rağmen verilerin test edilmesindeki performansı potansiyel aşırı uyum ve genellemede sınırlılıkları olduğunu göstermektedir. Bu nedenle, RF modelinde genelleştirilebilirlik için iyileştirme gerekmekte olup SVM ve KNN modelleri orta düzeyde tahmin performansına göstermiştir.

Araştırma bireylerin desteklenmesi ve sınav hazırlık süreçlerine yönelik hedeflenen stratejilerin geliştirilmesinde bilgi sağlayabilir. Aynı zamanda KPSS başarısını tahmin etmek için en uygun modelin seçilmesinde karar verme süreçlerine rehberlik edebilir. Sınav başarısını etkileyebilecek çalışma alışkanlıkları, sosyo-ekonomik ve psikolojik faktörler gibi değişkenlerin de dahil edilerek sınava girenlerin performansına ilişkin daha derinlemesine incelemeler yapılması önerilmektedir. Ayrıca, yordayıcılar arasındaki etkileşim etkilerinin araştırılması ve doğrusal olmayan ilişkilerin incelenmesi, KPSS başarısını etkileyen değişkenlerin daha kapsamlı anlaşılmasını sağlayabilir. Ek olarak, derin öğrenme ve gradyan artırma gibi yeni geliştirilen makine öğrenimi algoritmalarının uygulanabilirliğinin araştırılması da tahmin doğruluğunu artırabilir.