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A comparative machine learning analysis for forecasting university satisfaction scores in Türkiye using TUMA, YÖK, and URAP data (2016–2025)

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Abstract

Assessing university satisfaction levels is crucial for achieving expected performance from universities. In this regard, this study investigates the forecasting of satisfaction scores at universities in Türkiye. In the application stage, Türkiye University Satisfaction Survey (TUMA), Council of Higher Education (YÖK) Statistics, and University Ranking by Academic Performance (URAP) data were employed. This data covers the period between 2016-2025. Linear Regression, Random Forest, Gradient Boosting, Tree, Neural Network, and Support Vector Machine (SVM) machine learning algorithms were applied to predict satisfaction scores. The trials for each model were carried out using Orange version 3.39 on samples taken according to different satisfaction levels and university types. After that, the model performances were compared and the best trial results show that model performances differ according to institution and satisfaction level type. Thus, it was concluded that institutions need to use different models for their satisfaction score predictions, depending on the level of satisfaction and the type of university.

Keywords Forecasting, Machine Learning, University Satisfaction, TUMA, Student Satisfaction, Higher Education

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1. Introduction

Student satisfaction is a subjective evaluation of the learning process and is closely related to the clarity and extent to which expectations are met. Universities prioritize student satisfaction to enhance student loyalty and improve their standing relative to other institutions. In this regard, universities aim to increase their national and international reputation through the satisfaction levels they achieve in line with the opportunities they offer (Tatar et al., 2017). Accordingly, universities in Türkiye, like international institutions, are competing to increase student satisfaction. Therefore, regularly monitoring student satisfaction is important, and the TUMA research conducted by UniAr provides a valuable benchmarking tool for universities (Polatgil, 2025).

In this context, this study focuses on predicting university satisfaction scores using machine learning algorithms with TUMA satisfaction data. Furthermore, variables affecting student satisfaction, such as the number of students and academic staff, the number of students participating in exchange programs, and the URAP score, were considered. A sample was selected from state and private universities with the best, medium, and worst scores, and six different machine learning algorithms were applied, and the results were compared. The results obtained are considered to be indicative for decision-makers and are thought to play an important role in achieving success in this competitive environment. The following parts of this paper are organized as follows: The next part provides a literature review about the topic. The section on methods in part 3 covers the dataset and machine learning algorithms used in the study. The results obtained from the application are discussed in section 4. The last part addresses the conclusions and recommendations for future research.

2. Literature Review

This section examines relevant studies in two subsections. The first subsection covers studies that use machine learning in university rankings and student satisfaction. The second subsection examines studies that use TUMA data.

This part summarizes selected studies that use machine learning in university rankings and student satisfaction data. In this context, Ho et al. (2021) focused on emergency distance learning satisfaction at a university in Hong Kong. They compared the performance of multiple regression and different machine learning models before and after applying random forest-based feature selection. Abdelkader et al. (2022) proposed a model for predicting student satisfaction levels in online learning during the COVID-19 period. In the mean time, Estrada-Real & Cantu-Ortiz (2022) have developed a predictive approach to forecast university rankings in the QS World University Rankings. Also, Go et al. (2023) attempted to predict e-learning satisfaction at a higher education institution in the Philippines using a data mining approach. Wardley et al. (2024) collected data from 49 Canadian universities, categorized it, and used machine learning techniques to predict university rankings. Moreover, Wisaeng & Muangmeesri (2025) used Times Higher Education data in their work and proposed a statistical and machine learning-based approach. Ahmed et al. (2025) have focused on their work predicting academic performance in higher education. Overall, while this sub-section presents general machine learning-focused studies, the following subsection focuses on TUMA-based studies.

This sub-section presents some recent studies that utilize TUMA data. In multi-criteria decision-making, the Two-layer Copeland approach, which considers different methods under a two-layered structure, was tested by Polatgil & Güler (2024) using TUMA 2022 data. Aydın (2024) has addressed the complementary mixed model. In the study, performance scores were generated from TUMA and URAP indicators using data from research universities in Türkiye over the last three years. Özdemir (2025) analyzed TUMA data with academic and institutional inputs using Data Envelopment Analysis. Polatgil (2025) investigated the change in student satisfaction using TUMA 2020-2024 data and analyzed satisfaction in six dimensions. Researcher examined the differences between years and dimensions using the Kruskal Wallis test. On the other hand, Güler (2025) first grouped private universities in terms of satisfaction using clustering analysis, and then ranked them using the FUCOM-PROMETHEE integrated method. The findings obtained were compared with TUMA data and found to be consistent. These studies are summarized in Table 1.

When both sections are considered together, it is observed that although machine learning methods are used to predict student satisfaction and university rankings, there is a gap in the field where TUMA data is used as shown in Table 1. In this direction, this study compares results obtained by using machine learning algorithms to predict satisfaction scores, considering TUMA and other institutional data. Thus, it contributes to the literature by providing decision support for higher education institutions.

Table 1. Summary of the Literature

Paper	**Data Source**	**Applied Method**
(Ho et al., 2021)	Student survey data	Regression and machine learning
(Estrada-Real & Cantu-Ortiz, 2022)	QS World University Rankings data	Statistical and machine learning methods
(Go et al., 2023)	Student survey data	Machine learning classifiers
(Wardley et al., 2024)	Canadian university ranking data	Machine learning models
(Abdelkader et al., 2022)	Student survey data	Feature selection and machine learning methods
(Ahmed et al., 2025)	Two student performance datasets	Regression Models and ensemble voting regressor
(Wisaeng & Muangmeesri, 2025)	THE university ranking data	Hybrid feature selection and ML models
(Polatgil & Güler, 2024)	TUMA dataset	Integrated MCDM methods with Two-layer Copeland
(Aydın, 2024)	URAP and TUMA data	Performance-based analysis
(Özdemir, 2025)	Higher education index and TUMA	Data Envelopment Analysis (DEA)
(Polatgil, 2025)	TUMA dataset	Statistical analysis
(Güler, 2025)	TUMA dataset	Clustering and MCDM methods
Proposed Study (2026)	*TUMA dataset*	*Machine Learning Algorithms*

3. Material and Method

This section contains two subsections, which are as follows: the first section presents details about the dataset used in the study, while the second part shares the machine learning algorithms applied.

3.1. Dataset

The study utilized the ten-year TUMA satisfaction data for the years 2016-2025 conducted by ÜniAr. TUMA (ÜniAr, 2024) overall satisfaction score includes sub-dimensions such as satisfaction with the learning experience, campus and life satisfaction, academic support and attention, satisfaction with the institution's management and operation, richness of learning opportunities and resources, and personal development and career support. In the published report, universities are clustered according to score ranges. Within the scope of this study, three universities were sampled separately from state and private universities from the A+, C, and FF clusters representing the highest, middle, and lowest scores, respectively. A total of eighteen universities were included in the evaluation. Institutional data affecting satisfaction for these universities, such as the number of students, number of academic staff, and number of students participating in exchange programs, were obtained from the YÖK statistics (YÖK, n.d.) website. URAP (URAP, n.d.) scores, which use academic performance in the ranking, were also included in the dataset. In line with the results obtained in the study, the general data set for the university with the best result for the SU1 group in the A+ category is presented in Table 2 as an example.

Using the dataset, the most successful model for predicting the satisfaction score for the following year using data from the previous years was searched for each institution. Accordingly, different machine learning algorithms were tested, and Orange version 3.39 was used in these tests. In this program, after loading the data, year+1score has been set as the target value. Firstly, normalization and completion of missing data were applied in the data preprocessing step. At this stage, the preprocess widget in Orange was used. Thus, missing values were imputed using mean values and features were normalized to the [0,1] range. Then, fifty percent of the dataset was designated as training data and 50% as test data, and six different algorithms were applied. The model performances obtained as a result of the application were recorded and the results were compared. The steps of this applied methodology are summarized in Figure 1.

Table 2. Satisfaction Score Dataset for A Sample University

Year	University	Institution Type	Overall Satisfaction Score	YEAR+1 Score	Level	Number of Students	Number of Students Participating in Exchange Programs	Number of Academic Staff	URAP Score
2016	SU1	State	491	462	A	59182	174	3175	656
2017	SU1	State	462	471	B	62580	394	3087	655
2018	SU1	State	471	482	B	63255	278	3112	685
2019	SU1	State	482	499	A	59162	280	3181	672
2020	SU1	State	499	498	A	58251	160	3215	678
2021	SU1	State	498	500	A	57808	107	3239	671
2022	SU1	State	500	510	A	55659	85	3308	667
2023	SU1	State	510	511	A+	56453	173	3180	967
2024	SU1	State	511	510	A+	55343	303	3085	979
2025	SU1	State	510	?	A+	53755	413	2980	856

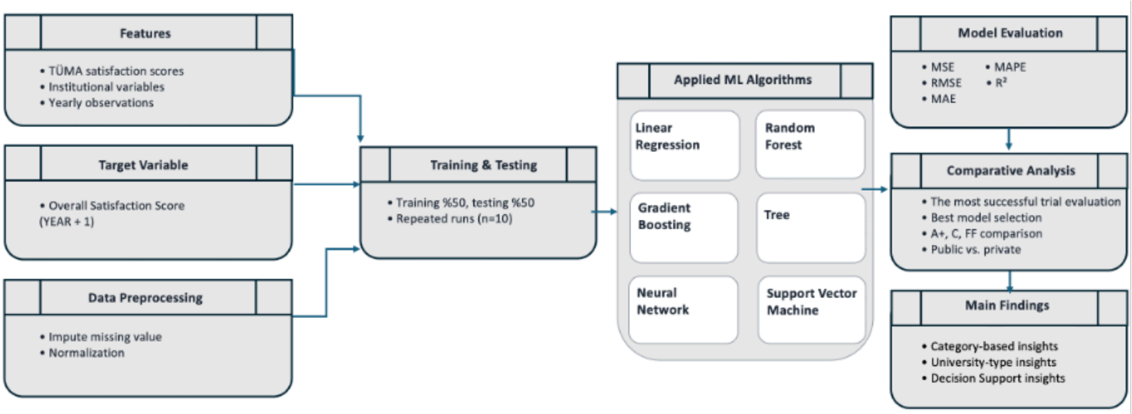

Figure 1. Machine Learning-based Analysis Framework

3.2. Applied Machine Learning Algorithms

The machine learning algorithms applied within the scope of the study are listed below:

- Linear Regression: In this type of model, a linear relationship between independent and dependent variables is assumed (Göksu et al., 2025).
- Random Forest: This algorithm, which uses regression and classification, is an ensemble method that combines outputs from different models. The method creates trees that result in a forest. As the number of trees increases, prediction accuracy improves (Jogunuri et al., 2024).
- Gradient Boosting: In this method, models are created sequentially, aiming to reduce errors made in the previous model. It produces highly accurate results in structured data sets (Okurlar & Eroğlu, 2025).
- Tree: The decision tree, which is part of supervised learning, is an algorithm that can be applied to classification and regression problems (Bansal et al., 2022).
- Neural Network: This algorithm aims high prediction accuracy by learning nonlinear relationships and complex structures through its layered structure composed of interconnected nodes (Okurlar & Eroğlu, 2025).
- SVM: This algorithm can be applied to both regression and classification problems. In this algorithm, there is a decision boundary that separates the classes, thus facilitating the placement of a new point into an appropriate category (Bansal et al., 2022).

The hyperparameter values for the applied models are given in Table 3.

Table 3. Hyperparameter Values for Models

Applied Algorithm	Hyperparameter Values
Linear Regression	Lasso Regression Regularization Strength: alpha-0.4 Elastic Net Mixing: 0.50:0.50
Random Forest	Number of Trees: 250 Limit depth of individual trees: 2 Do not split subsets smaller than: 3
Gradient Boosting	Number of Trees: 100 Learning rate: 0.100 Limit depth of individual trees: 3

Applied Algorithm	Hyperparameter Values
	Do not split subsets smaller than: 2
	Subsampling: 0.80
Tree	Min Number of Instances: 2
	Do not split subsets smaller than: 4
	Limit the maximal tree depth: 4
Neural Network	Neurons in hidden layers: 5
	Activation: ReLu
	Solver: L-BFGS-B
	Regularization, a=0.01
	Max Number of Iterations: 1000
SVM	Cost (C): 1
	Regression loss epsilon: 0.10
	Kernel: Linear
	Numerical Tolerance: 0.0010
	Iteration Limit: 1000

4. Result and Discussion

This section first introduces the metrics used to evaluate model performance. Then, the application results are presented and discussed in a comparative manner. The metrics described below were used to demonstrate the success of the results obtained from the machine learning algorithms used in the study (Göksu et al., 2025):

- Mean Absolute Error (MAE): It is calculated by taking the average of the absolute values of the differences between the predicted and observed values. This shows the extent to which the predictions deviate from the actual values. Lower MAE values indicate higher prediction accuracy.
- Mean Squared Error (MSE): In this metric, the differences between the prediction and the actual value are squared and averaged. Low MSE values indicate better performance.
- Root Mean Squared Error (RMSE): This method provides errors in real units by calculating the square root of the MSE, hence facilitating comprehension. A low RMSE value indicates superior performance.
- R-squared (R2): R2 indicates the model's level of data explanation. Approaching 1 indicates high explanatory power, while approaching 0 indicates low explanatory power.
- Mean Absolute Percentage Error (MAPE): The percentage of deviation between predictions and actual values is expressed as MAPE. Smaller MAPE values indicate better model performance. In this metric, the lower bound is 0, while there is no upper bound.

The formulas provided below have been used to calculate these metrics. In these formulas, observed values are shown by for the predicted value, for the mean of the observed values and n is the number of observation (Atalan et al., 2025).

MSE is calculated using Eq. 1.

$$\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{1}$$

RMSE calculation is performed using Eq. 2.

$$\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \tag{2}$$

MAE value is found using Eq. 3.

$$\frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{3}$$

MAPE is determined through Eq. 4.

$$\frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{4}$$

R^2 is obtained by applying Eq. 5.

$$1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2} \tag{5}$$

After running the models 10 times for each university, the most successful trial results for each model from state and private universities are shared comparatively in Table 4, Table 5, and Table 6. In the tables, SU represents the relevant state university, and PU represents the private university.

Table 4. The Best Results in the Tests for A+ Category

	SU1					PU1				
	MSE	RMSE	MAE	MAPE	R^2	MSE	RMSE	MAE	MAPE	R^2
Linear Regression	56.869	7.541	6.299	1.286	0.744	168.199	12.969	8.017	1.688	0.550
Random Forest	76.915	8.770	8.195	1.686	0.669	63.695	7.981	5.901	1.213	0.489
Gradient Boosting	38.412	6.198	5.968	1.225	0.835	64.016	8.001	5.509	1.128	0.487
Tree	46.597	6.826	6.000	1.229	0.799	111.75	10.571	7.750	1.607	0.701
Neural Network	11.087	3.330	2.614	0.520	0.966	145.910	12.079	9.078	1.892	0.610
SVM	12.743	3.570	2.808	0.572	0.872	171.086	13.080	8.998	1.890	0.528

Table 5. The Best Results in the Tests for C Category

	SU1					PU1				
	MSE	RMSE	MAE	MAPE	R^2	MSE	RMSE	MAE	MAPE	R^2
Linear Regression	172.757	13.144	9.250	1.905	0.797	103.004	10.149	9.444	2.015	0.874
Random Forest	16.063	4.008	3.412	0.757	0.943	29.677	5.448	4.630	0.97	0.964
Gradient Boosting	50.816	7.129	6.146	1.366	0.819	273.678	16.543	15.008	3.121	0.665
Tree	178.014	13.342	8.833	1.818	0.796	104.306	10.213	7.417	1.490	0.872
Neural Network	111.500	10.559	8.265	1.726	0.872	947.090	30.775	25.575	5.455	0.180
SVM	178.262	13.351	9.927	2.073	0.791	476.518	21.829	17.538	3.590	0.753

Table 6. The Best Results in the Tests for FF Category

	SU1					PU1				
	MSE	RMSE	MAE	MAPE	R^2	MSE	RMSE	MAE	MAPE	R^2
Linear Regression	150.045	12.249	10.741	4.631	0.622	443.138	21.051	18.884	5.017	0.610
Random Forest	284.699	16.873	16.545	7.077	0.282	11.271	3.357	2.688	0.786	0.978
Gradient Boosting	14.214	3.770	2.963	1.300	0.857	72.943	8.541	5.902	1.688	0.915
Tree	91.181	9.549	8.667	3.772	0.701	210.972	14.525	12.250	3.301	0.831
Neural Network	128.007	11.314	8.756	3.859	0.580	347.157	18.632	15.833	4.508	0.506
SVM	140.499	11.853	9.667	4.225	0.570	311.218	17.641	15.795	4.321	0.636

When examining the results obtained by university and category, it is seen that the models yield successful results for state and private universities in the A+ category, which has a high satisfaction score. In the SU1 group, the artificial neural network model was the most successful model with the lowest error and highest R^2 value, followed by the SVM model with similar results. On the other hand, in the PU1 group, which is in the same category, it is seen that, compared to SU1, error values generally increased and R^2 values yielded low results, thus the models yielded worse results. While the models generally produced successful results in this category, performance differences were observed in the state and private groups.

In the SU2 group of category C, the Random Forest model performed better than other models. The low error rates and high R^2 values, which indicate the model's explanatory power, demonstrate the model's success in this group. Similarly, the Random Forest model also achieved the best results in the PU2 group. However, in other models, error rates generally increased and R^2 values decreased. According to the results in the FF category, the Gradient Boosting model performed better in the SU3 group. Other models showed increased error values and decreased R^2 values. In the PU3 group, the Random Forest model produced more successful results in prediction, indicating differences between the two groups.

When the results of the three categories are considered together, it is seen that the predictability of satisfaction scores varies by category and institution as shown in Figure 2. In state universities, model performance varies as satisfaction levels decline. In private universities, it has been concluded that some models produce more successful results despite declining satisfaction levels.

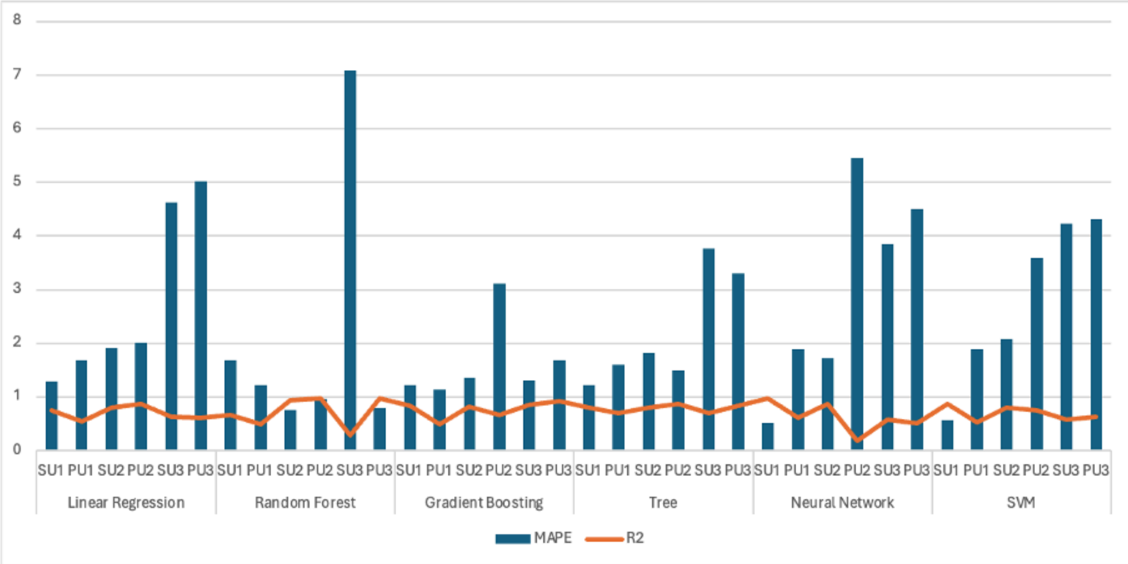

Figure 2. Performance Comparison of Models

5. Conclusion

This study focuses on predicting university satisfaction scores using machine learning methods based on TUMA data and variables affecting satisfaction. The models were applied separately for different satisfaction levels and university types on the samples taken. Based on the findings, it is observed that model predictions give successful results in the A+ category, which has a high level of satisfaction, but model performance differs for two different types of universities in the same group. In the state university group of category C, it is observed that the performance of models such as artificial neural networks and SVM, which gave the most successful results in the A+ category, decreased. In the private university group, error rates mostly increased compared to the first category, but model explanatory values also increased. When examining the FF category, two different models, Gradient Boosting and Random Forest, provided the most successful results on a group basis.

When the three categories and groups are evaluated together, it shows that a single model is insufficient for predicting satisfaction scores. In this regard, the variability in model performance along with the satisfaction level indicates that the data, institution types, and other input variables also have an effect on the models. Based on the results obtained, it was concluded that decision-makers should determine their strategies using different prediction models according to category and university type.

Also, the study's limitations include its data set consisting of universities in Türkiye. On the other hand, the indicators used are also among the limitations, since they can be expanded. Another limitation is that more advanced approaches, such as deep learning or hybrid models, have not been examined. In future studies, including more years in the dataset will enable different analyses to be performed. Developing hybrid models based on university type or category could also be considered among the different options. Additionaly, the effects on model performance can be examined by incorporating different indicators and variables specific to institutions.

Declarations

Conflict of interest The author(s) have no competing interests to declare that are relevant to the content of this article.

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