

MAN456 - Business Analytics

Final Project

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Introduction

In this project, we analyze the daily meal distribution data from Bilkent University’s main cafeteria, collected between December 26, 2022, and December 31, 2024, covering approximately two years of cafeteria operations across four academic periods.

The dataset includes detailed information on the daily lunch and dinner menus, broken down into four components: soup, main dish, side dish, and dessert (or fruit/appetizer options). Alongside the menus, the number of people who purchased meals for each session (lunch and dinner) is recorded. The dataset is organized by us before processing. You can see the examples of the dataset before and after process below. You can see the full-sized images in the Appendix .

MERKEZ - DOĞU KAMPÜS GÜNLÜK SATIŞ BİLGİLERİ											
MARMARA RESTORAN											
TARİH	SABAH KAHVALTI	KAHVALTI TOPLAM	FIX ÖDLE	KUMANYA ÖDLE	FIX AŞAM	KUMANYA AŞAM	FIXS TOPLAM	SEÇMELİ ÖDLE	SEÇMELİ AŞAM	SEÇMELİ TOPLAM (Aşam Yemeli)	TOPLAM KUYER
1/12/2024	9	9	182	0	199	0	381	82	216	298	679
10/12/2024	28	28	640	3	489	0	1112	78	82	160	1272
13/12/2024	20	20	340	6	521	0	876	272	120	399	1269
14/12/2024	21	21	419	7	502	0	924	107	142	249	873
16/12/2024	20	20	406	9	324	0	749	92	33	125	874
16/12/2024	10	10	84	0	185	0	279	95	22	117	396
17/12/2024	8	8	110	0	120	0	230	19	31	50	280
18/12/2024	11	11	163	3	130	1	287	128	27	155	442
19/12/2024	4	4	271	2	114	0	387	83	32	95	472
19/12/2024	5	5	190	3	59	0	252	58	53	111	363
19/12/2024	3	3	118	0	88	0	214	169	17	172	393
19/12/2024	8	8	169	5	87	1	242	56	23	79	321
19/12/2024	5	5	31	0	26	0	56	20	7	27	83
19/12/2024	3	3	27	0	64	2	93	12	6	18	121
19/12/2024	2	2	808	3	62	0	873	60	18	78	951
19/12/2024	3	3	707	3	119	1	830	84	2	86	916
19/12/2024	4	4	765	4	49	0	818	63	38	101	919
19/12/2024	4	4	735	0	92	2	819	94	12	106	929
19/12/2024	1	1	184	4	76	2	266	41	5	46	312
19/12/2024	4	4	34	4	20	0	58	12	17	29	87
19/12/2024	3	3	35	0	55	0	90	8	1	9	99
19/12/2024	2	2	93	3	116	3	215	112	11	123	338
19/12/2024	1	1	189	14	113	0	296	53	9	62	358
19/12/2024	9	9	148	8	92	0	248	71	18	89	337
19/12/2024	1	1	185	0	124	1	311	97	9	106	417
19/12/2024	5	5	190	3	155	0	349	129	17	145	494
19/12/2024	2	2	124	0	151	0	275	14	9	23	298
19/12/2024	6	6	149	0	155	0	304	10	84	94	208
19/12/2024	41	41	1514	1	817	0	2332	215	65	271	2644
19/12/2024	42	42	888	2	681	0	1561	507	92	600	2161
19/12/2024	37	37	1525	29	763	1	2318	97	78	175	2493
TOPLAMLAR	322	322	9	115	6238	14	17705	2645	5288	4133	21638

(a) Fix Sale

MERKEZ - DOĞU KAMPÜS GÜNLÜK SATIŞ BİLGİLERİ											
MARMARA RESTORAN											
TARİH	SABAH KAHVALTI	KAHVALTI TOPLAM	FIX ÖDLE	KUMANYA ÖDLE	FIX AŞAM	KUMANYA AŞAM	FIXS TOPLAM	SEÇMELİ ÖDLE	SEÇMELİ AŞAM	SEÇMELİ TOPLAM (Aşam Yemeli)	TOPLAM KUYER
1/12/2024	9	9	182	0	199	0	381	82	216	298	679
10/12/2024	28	28	640	3	489	0	1112	78	82	160	1272
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14/12/2024	21	21	419	7	502	0	924	107	142	249	873
16/12/2024	20	20	406	9	324	0	749	92	33	125	874
16/12/2024	10	10	84	0	185	0	279	95	22	117	396
17/12/2024	8	8	110	0	120	0	230	19	31	50	280
18/12/2024	11	11	163	3	130	1	287	128	27	155	442
19/12/2024	4	4	271	2	114	0	387	83	32	95	472
19/12/2024	5	5	190	3	59	0	252	58	53	111	363
19/12/2024	3	3	118	0	88	0	214	169	17	172	393
19/12/2024	8	8	169	5	87	1	242	56	23	79	321
19/12/2024	5	5	31	0	26	0	56	20	7	27	83
19/12/2024	3	3	27	0	64	2	93	12	6	18	121
19/12/2024	2	2	808	3	62	0	873	60	18	78	951
19/12/2024	3	3	707	3	119	1	830	84	2	86	916
19/12/2024	4	4	765	4	49	0	818	63	38	101	919
19/12/2024	4	4	735	0	92	2	819	94	12	106	929
19/12/2024	1	1	184	4	76	2	266	41	5	46	312
19/12/2024	4	4	34	4	20	0	58	12	17	29	87
19/12/2024	3	3	35	0	55	0	90	8	1	9	99
19/12/2024	2	2	93	3	116	3	215	112	11	123	338
19/12/2024	1	1	189	14	113	0	296	53	9	62	358
19/12/2024	9	9	148	8	92	0	248	71	18	89	337
19/12/2024	1	1	185	0	124	1	311	97	9	106	417
19/12/2024	5	5	190	3	155	0	349	129	17	145	494
19/12/2024	2	2	124	0	151	0	275	14	9	23	298
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19/12/2024	42	42	888	2	681	0	1561	507	92	600	2161
19/12/2024	37	37	1525	29	763	1	2318	97	78	175	2493
TOPLAMLAR	322	322	9	115	6238	14	17705	2645	5288	4133	21638

(b) Menu

Figure 1: Unprocessed Data

Date	i_evening	Soup	Main Dish	Side Dish	Extra Dish	Day of Week	Fix_Value
2023-01-01 00:00:00	0	KARNABAHAAR ÇORBA	İZMİR KÖFTE	BULGUR PİLAVI	YOĞURT	Sunday	243
2023-01-01 00:00:00	1	KÖYLÜ ÇORBA	KIYMALI İSPANAK (YOĞURT)	SU BÖREĞİ	ELMA	Sunday	257
2023-01-02 00:00:00	0	MISIR ÇORBA	ŞİCİLİYA USULÜ TAVUK (PÜRE)	AKDENİZ SALATA	SÜTLAÇ	Monday	818
2023-01-02 00:00:00	1	TARHANA ÇORBA	TAS KEBABI	ŞEH. PİRİNÇ PİLAVI	BAHÇE SALATA	Monday	773
2023-01-03 00:00:00	1	MERCİMEK ÇORBA	KÖRİ SOSLU KÖFTE	KAŞARLI ERIŞTE	ÇIKOLATALI İRMİK TATLISI	Tuesday	869
2023-01-03 00:00:00	0	SEBZE ÇORBA	ETLİ KURU FASULYE	BULGUR PİLAVI	TURŞU	Tuesday	425
2023-01-04 00:00:00	0	ALACA ÇORBA	ORMAN KEBAP	SPAGETTİ NAPOLİTEN	AYRAN	Wednesday	658
2023-01-04 00:00:00	1	YAYLA ÇORBA	KARIŞIK MUSAKKA	PEYNİRLİ RULO BÖREK	PORTAKAL	Wednesday	310
2023-01-05 00:00:00	1	DOMATES ÇORBA	PİLİÇ ROTİ (SEBZE HAŞLAMA)	BULGUR PİLAVI	YOĞURT	Thursday	694
2023-01-05 00:00:00	0	ŞEHRİYE ÇORBA	MEKSIKA KÖFTE (PATATES KAVURMA)	KARIŞIK SALATA	TULUMBA TATLISI	Thursday	731
2023-01-06 00:00:00	0	EZOĞELİN ÇORBA	KIYMALI İSPANAK (YOĞURT)	PEYNİRLİ GÜL BÖREĞİ	MANDALİNA	Friday	345
2023-01-06 00:00:00	1	KEREVİZ ÇORBA	ANKARA TAVA	MEVSİM SALATA	ELBASAN TATLISI	Friday	662
2023-01-07 00:00:00	1	MANTAR ÇORBA	KARIŞIK SEBZE GRATEN	YOĞURTLU MAKARNA	ELMA	Saturday	369
2023-01-07 00:00:00	0	ŞAFAK ÇORBA	TATLI - EKŞİ SOSLU TAVUK (DOM. PİRİNÇ PİLAVI)	AYRAN	ÇIKOLATALI PUDİNG	Saturday	464
2023-01-08 00:00:00	1	AYRANAŞI ÇORBA	ELBASAN KÖFTE	KAŞARLI CEVİZLİ ERIŞTE	AMASRA SALATA	Sunday	289
2023-01-08 00:00:00	0	BULGUR ÇORBA	ETLİ TAZE FASULYE	ARPA ŞEHRİYE PİLAVI	MUZ	Sunday	146
2023-01-09 00:00:00	0	İSPANAK ÇORBA	ET SOTE (PATATES KAVURMA)	AYRAN	MUHALLEBİLİ CEZERYE	Monday	404
2023-01-09 00:00:00	1	TARHANA ÇORBA	PİLİÇ KAVURMA (SEBZE HAŞLAMA)	PİRİNÇ PİLAVI	BAHÇE SALATA	Monday	275
2023-01-10 00:00:00	1	ALACA ÇORBA	KIYMALI TÖRLÜ	İSPANAKLI RULO BÖREK	MANDALİNA	Tuesday	101
2023-01-10 00:00:00	0	EKŞİLİ ANADOLU ÇORBA	İZMİR KÖFTE	PEYNİRLİ SPAGETTİ	SUP	Tuesday	311
2023-01-11 00:00:00	0	MERCİMEK ÇORBA	ETLİ BEZELYE	ŞEH. PİRİNÇ PİLAVI	YOĞURT	Wednesday	243
2023-01-11 00:00:00	1	MİNESTRONE ÇORBA	ET SOTE (PATATES KAVURMA)	NİŞ SALATA	KAHVELİ KARAMELLİ ŞARLOT	Wednesday	120
2023-01-12 00:00:00	0	KÖYLÜ ÇORBA	PİLİÇ BAGET (PÜRE)	ZY. TAZE FASULYE	FINDIKPARE	Thursday	219
2023-01-12 00:00:00	1	YOĞURT ÇORBA	KARIŞIK MUSAKKA	PATATESLİ RULO BÖREK	PORTAKAL	Thursday	57
2023-01-13 00:00:00	1	KİLİS ÇORBA	ÇİFTLİK KÖFTE	PİRİNÇ PİLAVI	YOĞURT	Friday	82
2023-01-13 00:00:00	0	LEBENİ ÇORBA	KIYMALI FIRIN PATATES	PEYNİRLİ MAKARNA	MEVSİM SALATA	Friday	164
2023-01-14 00:00:00	1	EZOĞELİN ÇORBA	KITIR PİLİÇ (SEBZE HAŞLAMA)	KAŞARLI ERIŞTE	KAZANDİBİ	Saturday	94
2023-01-14 00:00:00	0	SEBZE ÇORBA	İZMİR KÖFTE	BULGUR PİLAVI	AYRAN	Saturday	425

Figure 2: Dataset after processing

Additions to the Dataset:

To enhance the dataset’s usability and ensure more accurate analysis, several modifications and additions were made. These adjustments help improve the consistency and clarity of the data, enabling better insights into meal patterns and attendance. Holiday dates are especially important for forecasting demand. Therefore, we found and added these features. The following additions were applied:

- Annotate special periods such as national holidays, Ramadan, and final exam periods.
- Outlier detection is done and eliminated from the dataset (Earthquake in 2023).
- Data is segmented according to academic semesters: Fall, Spring, Summer, Summer Holiday and Winter Break.
- Since some food, such as Helva and Turşu, only appear with specific Main Dishes, we eliminated these correlated features after one-hot encoding.
- Different variations of chicken, meatball, and fish dishes are consolidated into the ‘*main_dish_chicken*’, ‘*main_dish_meatball*’, and ‘*main_dish_fish*’ columns. For example, dishes like ‘Piliç Roti’ and ‘Piliç Kavurma’ are categorized under ‘*main_dish_chicken*’ rather than being listed as separate entries.

- Extra Dish and Side Dish might contain the same dishes; therefore, we one-hot encoded them together.
- All different salad items are consolidated into the one salad column.

The academic calendar is defined as follows:

Academic Calendar

2022–2023 Academic Year

- **Fall Semester:** Until January 9, 2023
Final Exams: December 26, 2022 – January 9, 2023
- **Spring Semester:** January 30, 2023 – June 16, 2023
Final Exams: June 4 – June 16, 2023
- **Summer Term:** July 3, 2023 – August 15, 2023
Final Exams: August 12 – August 15, 2023

2023–2024 Academic Year

- **Fall Semester:** September 14, 2023 – January 6, 2024
Final Exams: December 22, 2023 – January 6, 2024
- **Spring Semester:** January 29, 2024 – June 1, 2024
Final Exams: May 20 – June 1, 2024
- **Summer Term:** June 10, 2024 – August 6, 2024
Final Exams: August 3 – August 6, 2024

2024–2025 Academic Year

- **Fall Semester:** September 16, 2024 – January 8, 2025
Final Exams: December 26, 2024 – January 8, 2025

This segmentation allows us to analyze potential differences in cafeteria usage across regular academic periods, final exam periods, and special event days.

Through predictive modeling and exploratory analysis, our study aims to understand how different factors — such as semester timing, final exams, Ramadan, day of the week, and

menu composition — influence cafeteria participation. We aim to predict daily meal demand more accurately, identify the menu components that attract higher or lower participation, and ultimately offer recommendations to minimize food waste and improve service planning. Our last dataset attributes look like this before One-Hot encoding them.

Variable	Type	Usage	Description
<i>Is_evening?</i>	Boolean	Input	Indicates whether the meal is an evening meal or lunch.
<i>Soup</i>	Categorical	Input	Soup served in the menu.
<i>Main Dish</i>	Categorical	Input	Main dish served in the menu.
<i>Side Dish</i>	Categorical	Input	Side dish served in the menu.
<i>Extra Dish</i>	Categorical	Input	Additional dish served in the menu.
<i>Day of Week</i>	Categorical	Input	Day of the week (Monday to Friday).
<i>Is_holiday?</i>	Boolean	Input	Indicates whether the day is a national holiday.
<i>Ramadan</i>	Boolean	Input	Indicates whether the day falls within Ramadan.
<i>Semester</i>	Categorical	Input	Academic semester at Bilkent University.
<i>Is_final_time?</i>	Boolean	Input	Indicates whether the day is during the final exam period.
<i>Month</i>	Categorical	Input	Month of the year.
<i>Year</i>	Categorical	Input	Year.
<i>Fix_Value</i>	Numerical	Output	Total demand for the fixed (set) menu.

Table 1: Description of Variables Used in the Dataset

Part 2

Problem Statement

Initially, the main identified problem was the unknown demand of the cafeteria, which could lead to two key issues:

- Customer dissatisfaction due to insufficient food availability during peak times.
- Food waste caused by preparing an excess of food that goes uneaten.

To address this, our objective was to investigate the factors that influence cafeteria use, with a particular focus on how different meals affect attendance, as well as to identify seasonal trends and special periods (such as exam weeks or holidays). Our goal was to analyze how these elements affect meal consumption patterns to inform more efficient meal planning and reduce waste.

The following questions were asked for the problem definition and the analysis was assessed to answer these.

- Which foods affect the number of people using the cafeteria on a given day ?
- Which periods, such as seasonality, holidays, exam periods, or Ramadan, significantly influence attendance patterns?

Initial Analysis of the Data

After the problem statement, we analyzed the assumptions and divided the data into several segments to assess the effects before applying analytical methods.

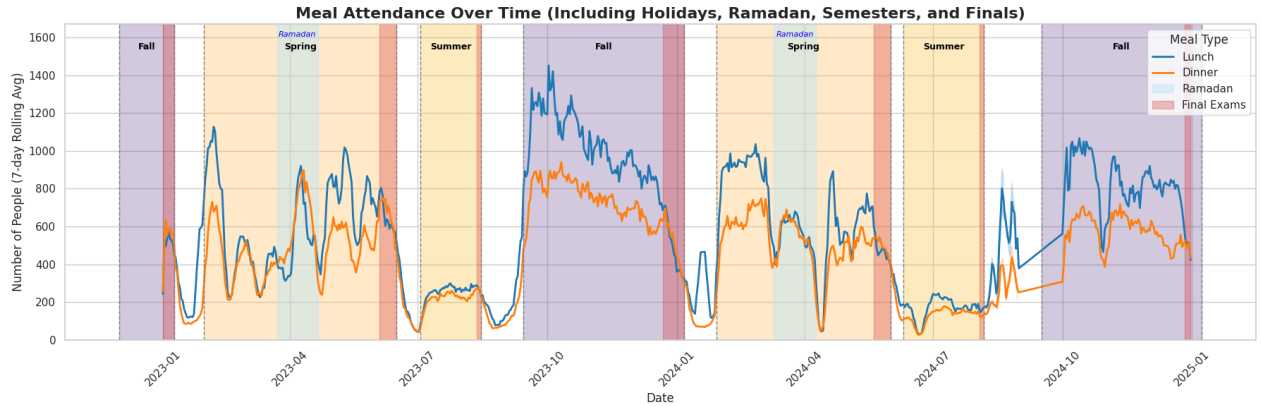


Figure 3: Meal Attendance Over Time

This figure shows meal attendance over time; including Ramadan, semesters and final periods. From this, we can observe the impact of these periods on attendance. It was seen that in each final season, meal attendance decreases; likely due to the end of classes and students leaving the dormitories.

We also observed that dinner attendance is generally lower than lunch attendance. However, during Ramadan, this trend reverses: dinner attendance rises to match or exceed lunch attendance, while lunch attendance drops. This shift aligns with expectations, as students fasting for Ramadan typically come to the cafeteria for dinner and skip lunch.

Additionally, some outliers were identified in the spring semester of 2023–2024, there was an unusually sharp decline in meal attendance. Upon further research, it was seen that this was likely influenced by the earthquake that occurred on February 6, 2023, which effected the semester. We treated this period as an outlier up until March 20, 2023. Other outliers were observed as sharp drops between semesters. To better understand these patterns, an additional graph showing the holiday periods was created.

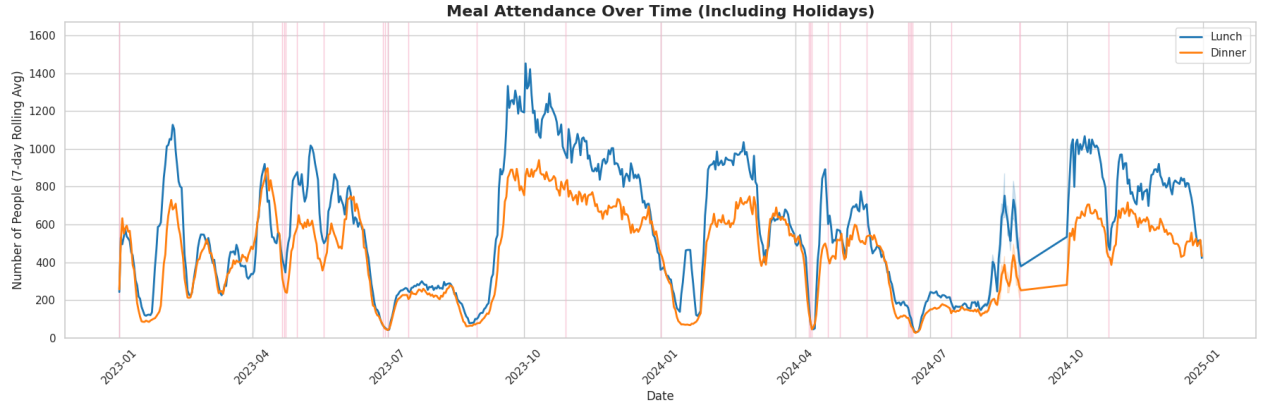


Figure 4: Meal Attendance Over Time Including Holidays

This figure shows that the drops in attendance coincide with designated holiday periods, confirming that holidays significantly impact meal attendance.

Part 3

Implementation of Analytic Methods

In this section, we experimented with several machine learning models, including Linear Regression, Random Forest, the Lasso variant of Linear Regression, and LightGBM. We used 80% of our dataset for training and 20% for testing. Given that we have many categorical variables (over 1000 after one-hot encoding), our models tended to overfit without feature selection. To mitigate this, we applied backwards elimination for the Linear Regression, while the other models inherently handle feature selection. Additionally, we found that applying a log transformation to the target variable (Y) significantly improved the model's performance, as it helped to stabilize the variance and make the data more normally distributed. The test dataset scores of the models we tried will be compared in the Comparison of the Models section.

Linear Regression

We applied Linear Regression with all the Features first. Then get the results below.

Model:	OLS	Adj. R-squared:	0.652
Dependent Variable:	Fix_Value	AIC:	2130.3425
Date:	2025-05-02 11:45	BIC:	3202.2555
No. Observations:	1081	Log-Likelihood:	-850.17
Df Model:	214	F-statistic:	10.47
Df Residuals:	866	Prob (F-statistic):	3.27e-141
R-squared:	0.721	Scale:	0.35233

Figure 5: Linear Regression

The high difference between R-square and adjusted R-square is caused by the high number of variables. Therefore, we applied backwards elimination with a significance level of 0.05.

Model:	OLS	Adj. R-squared:	0.675
Dependent Variable:	Fix_Value	AIC:	1902.2508
Date:	2025-05-02 11:46	BIC:	2081.7339
No. Observations:	1081	Log-Likelihood:	-915.13
Df Model:	35	F-statistic:	65.09
Df Residuals:	1045	Prob (F-statistic):	6.37e-235
R-squared:	0.686	Scale:	0.32926

Figure 6: Linear Regression after backward elimination

We used Cook's distance to identify additional outliers and eliminated the ones with Cook's distance higher than 0.02.

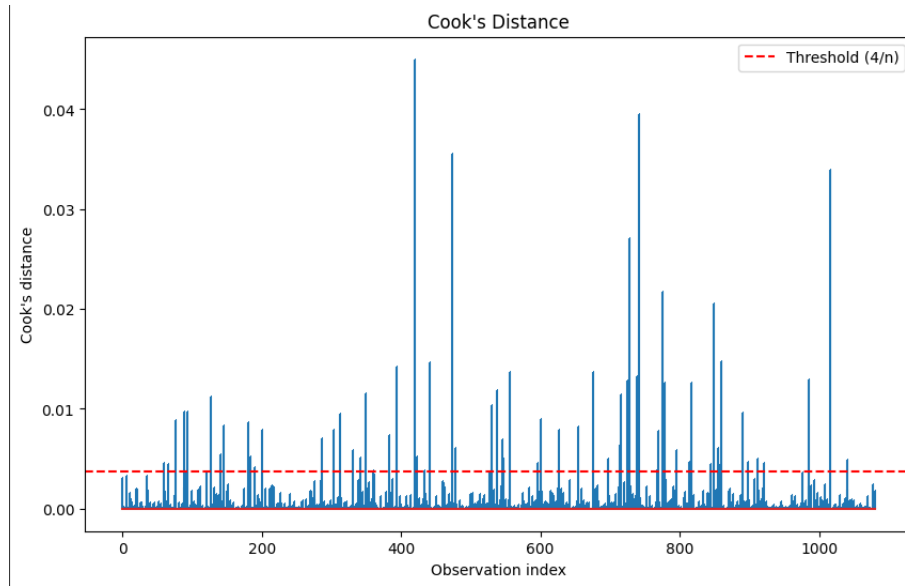


Figure 7: Cook's Distance

Then applied Linear Regression with backward elimination again.

Model:	OLS	Adj. R-squared:	0.702
Dependent Variable:	Fix_Value	AIC:	1796.1993
Date:	2025-05-02 11:50	BIC:	1970.4694
No. Observations:	1074	Log-Likelihood:	-863.10
Df Model:	34	F-statistic:	75.22
Df Residuals:	1039	Prob (F-statistic):	5.34e-253
R-squared:	0.711	Scale:	0.30195

Figure 8: Linear Regression after backward elimination

Our model significantly works better with additions we added.

Linear Regression with Lasso

We employed Lasso Regression not only to mitigate overfitting but also as a method for feature selection. By applying L1 regularisation, Lasso penalises the absolute size of the coefficients, effectively shrinking some of them to zero. This leads to a sparse model where only the most relevant features are retained, which is particularly useful in our case, given the high dimensionality introduced by one-hot encoding.

Results: Ordinary least squares			
Model:	OLS	Adj. R-squared:	0.698
Dependent Variable:	Fix_Value	AIC:	1822.6660
Date:	2025-05-02 11:51	BIC:	2066.6441
No. Observations:	1074	Log-Likelihood:	-862.33
Model:	48	F-statistic:	52.67
Residuals:	1025	Prob (F-statistic):	1.14e-240
R-squared:	0.712	Scale:	0.30564

Figure 9: Linear Regression after backward elimination

Random Forest

We utilized the Random Forest algorithm due to its robustness against overfitting and its ability to handle high-dimensional data effectively. As an ensemble of decision trees, Random Forest averages the predictions of multiple trees, reducing variance and improving generalization. Moreover, it inherently ranks features by their importance in predicting the target variable, which provides valuable insights into which variables contribute most to model performance. This makes Random Forest particularly suitable for our dataset, where numerous categorical features emerge from one-hot encoding.

For Random Forest and LightGBM, we applied `GridSearchCV` to tune our parameters. The best parameters for Random Forest are: `max_depth=None`, `min_samples_leaf=2`, `min_samples_split=10`, and `n_estimators=100`.

R-squared value for Random Forest (train) is 0.84

LightGBM

We chose LightGBM as one of our models due to its efficiency and ability to handle large-scale data with high cardinality, which fits our dataset that includes many one-hot encoded variables. LightGBM is a gradient boosting framework that grows trees leaf-wise, resulting in faster training and often higher accuracy compared to traditional boosting methods. It inherently deals with multicollinearity and captures non-linear relationships without requiring extensive preprocessing. Additionally, LightGBM is resistant to overfitting to some extent, but we still applied hyperparameter tuning through `GridSearchCV` to optimize its performance. Its built-in handling of categorical features and regularization terms helped improve generalization.

The best parameters found were: `learning_rate=0.1`, `max_depth=10`, `n_estimators=100`, `num_leaves=31`, and `subsample=0.8`. These settings improved both the accuracy and generalization capability of the model.

R-squared value for LightGBM (train) is 0.814

Comparison of the Models

Performance Measures	Linear Regression	Lasso	Random Forest	LightGBM
Train R-square	0.71	0.71	0.84	0.81
Test R-square	0.71	0.72	0.73	0.76
Test MSE	55024	53312.73	51155.94	45544.21
Test MAE	155	151.38	153.45	138.30
Test MAPE	51.76	51.82	65.25	54.5

Table 2: Model Comparison

Although Random Forest achieves the highest Train R-square, its performance drops on the test set, indicating slight overfitting. In contrast, LightGBM demonstrates better generalization, as reflected in its superior Test R-square, suggesting it captures the variance in the data more effectively. Furthermore, LightGBM significantly outperforms the other models in terms of both Mean Squared Error (MSE) and Mean Absolute Error (MAE), indicating more accurate and consistent predictions. Therefore, we decided to continue our project with LightGBM model.

Lastly, the MAPE values exceed 50%, indicating large percentage errors. However, this high error might be due to the small values of the target variable, where even minor deviations in predictions result in significant percentage changes in the error measure.

Part 4

Interpretation of the Results

Effects of the Variables

Since LightGBM doesn't include interpretable coefficients of the model as linear regression does, we used SHAP Values to understand the impact of features.

SHAP graph contains variables sorted by importance level in the Y axis, with the most important feature at the top and decreasing in importance toward the bottom. The top features have the largest overall impact on the predictions.

The X-axis contains SHAP values that indicate how much a feature contributed to pushing the prediction up or down for a specific observation. A positive SHAP value means the feature increased the predicted value, whereas a negative SHAP value means the feature

decreased the predicted value.

Since we used categorical variables only for modeling, the red dots show that the categorical variable exists (value = 1), and the blue dots mean it does not.

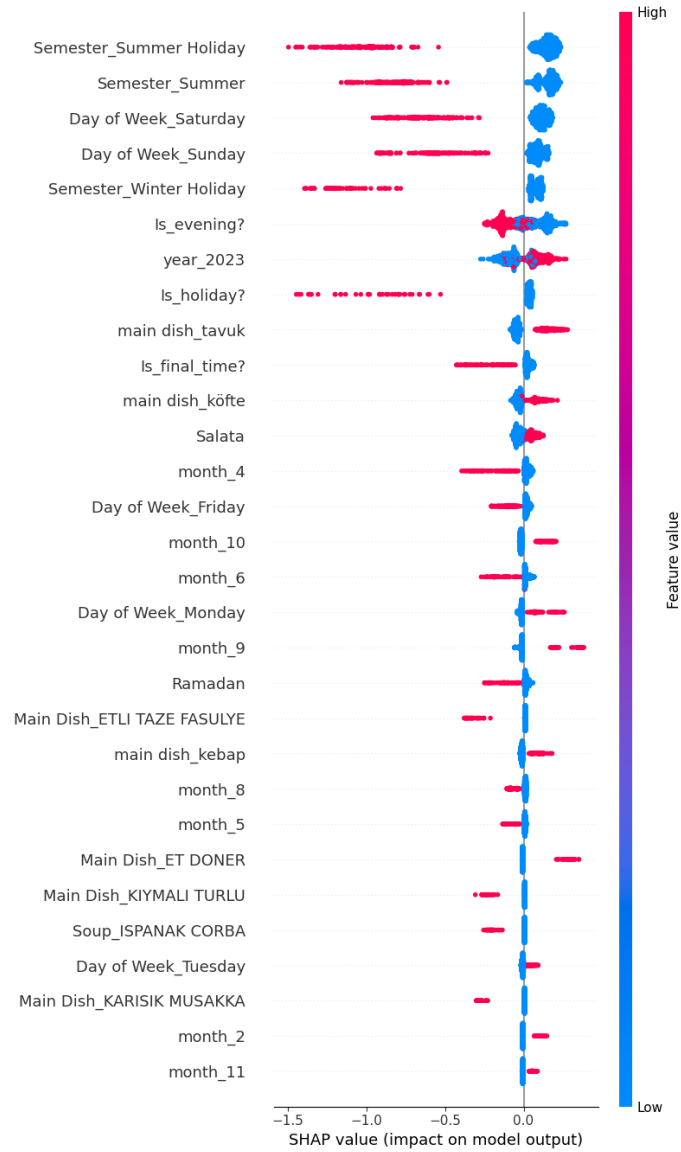


Figure 10: SHAP Graph - Top 20 Features

As shown in the SHAP graph above, the top 20 features are displayed. A graph with

additional features is also included in the appendix. From the graph, it is evident that the most important features are related to holiday variables, such as Summer Holiday, Summer Semester, Saturday, Sunday, and Winter Break. Red dots appear when these variables are active and it can be observed that SHAP values are significantly lower during these periods. Another important factor is the Evening feature, where the demand for evening meals is lower, as expected, since not all students remain for dinner in the evening. Additionally, the demand for 2023 was higher than for 2024, suggesting that if you plan to use the model for future years, such as 2025, the Year feature can be excluded.

Similar to other holidays, National Holidays and Final Exam periods also negatively impact demand, as many people return to their hometowns. Moreover, demand tends to be higher on Mondays and lower on Fridays, possibly reflecting students' schedules and routines. Also, Ramadan is an important feature since people don't prefer eating at lunch times when they feasting.

Menus containing chicken dishes, meatball dishes, kebabs, meat doner, and salads increase the demand as expected, whereas dishes like spinach soup, minced meat stew, beans, and mixed moussaka reduce the demand.

You can observe how other meals effects the demand in Appendix.

Moreover, for the initial questions we had for the analysis, the answers can be seen in the following table:

Table 3: Answers to Initial Questions

Question	Answer
Foods increasing attendance	Chicken, meatballs, kebabs, döner, salads ↑
Foods decreasing attendance	Spinach soup, minced stew, beans, moussaka ↓
Low-demand periods	Holidays, weekends, exams, Ramadan, evenings
High-demand days	Mondays
Low-demand days	Fridays

Benefits of the Model to the Cafeteria

To evaluate the benefits of our model, we assumed a scenario in which the cafeteria prepares a fixed number of meals each day. Days were divided into weekdays and weekends, and the fixed meal amounts were determined using the average number of people who received the fixed menu in the training dataset:

- 900 meals on weekdays

- 303 meals on weekends

To ensure a precise and unbiased evaluation, both the baseline and model predictions were tested only on days that were not during Ramadan, holidays, or the summer semester. These were excluded since demand patterns in these periods differ significantly.

The comparison between the fixed plan and the model’s output is summarized below:

Table 4: Comparison of Baseline vs. Model Plan Performance

Metric	Baseline Plan	Model Plan	Improvement
Waste (Weekday)	978 meals (15.3%)	212 meals (3.3%)	12.0% waste
Shortage (Weekday)	1059 meals (16.6%)	742 meals (11.6%)	5.0% shortage
Waste (Weekend)	757 meals (14.5%)	521 meals (10.0%)	4.5% waste
Shortage (Weekend)	1138 meals (21.8%)	609 meals (11.6%)	10.2% shortage

As seen in the table, the model significantly reduces both overproduction (waste) and underproduction (shortage) compared to the fixed plan. This can help the cafeteria:

- Minimize food waste and reduce unnecessary costs
- Avoid shortages that negatively impact students and staff
- Dynamically adjust meal and staffing plans to better reflect real demand

Because the analysis was performed on a restricted dataset, continuing to gather and update the data over time would result in more accurate and sustainable solutions. Furthermore, setting a minimum level of staff and meals for normal semester days could ensure that student and staff needs are met while reducing food waste and operating costs.

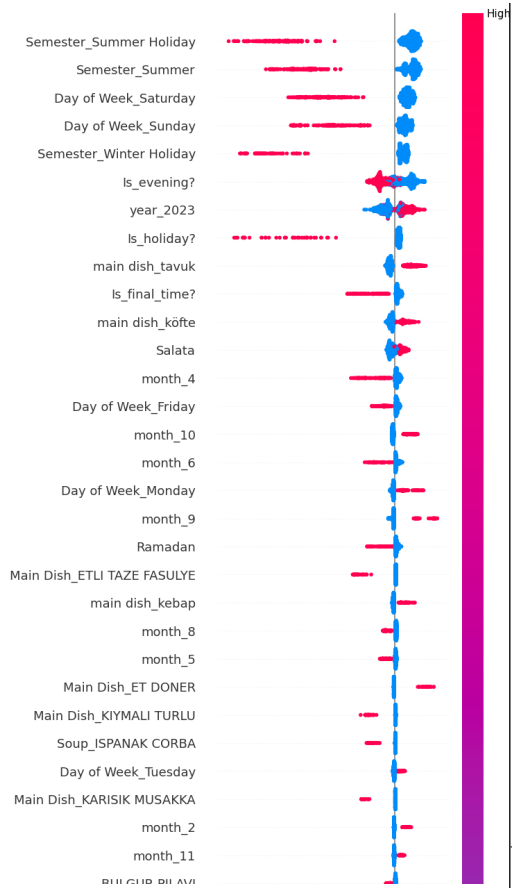
Appendix

ŞUBAT 2024 - FİKS MENU						
28/01/2024	30/01/2024	31/01/2024	01/02/2024	02/02/2024	03/02/2024	04/02/2024
YOĞURT ÇORBA KEREK KÖFTE (SEBZE HAŞLAMA) BULGUR PILAVI PORTAKAL	BULGUR ÇORBA KIYMALI SPANAK (YOĞURT) SU İÇİREBİLİ ELMA	YAVLA ÇORBA AÇI USULU TAVUK (PATATES TAVUK) KEÇİ SALATA ELMA	LEBENİ ÇORBA KARŞIK MUSAĞA SOSLU MAKARNA MUT	ŞEHİRİYE ÇORBA DÖNER KEBAB DOM. PİRİNÇ PILAVI PANCARLI BAĞIÇ SALATA MUT	MAINTAR ÇORBA KAŞARLI KÖFTE (SEBZE HAŞLAMA) ERİŞTE PORTAKAL	SEBZE ÇORBA ET'Lİ NOHUT BULGUR PILAVI YOĞURT
VEGAN MANTAR SÖTİ	VEGAN İSPANAK KAVURMA (YOĞURT)	VEGAN BROKOLİ	VEGAN KARŞIK MUSAĞA	VEGAN SEBZE KAVURMA (YOĞURT)	VEGAN YULPADA İSPANAKLI DOLMA	VEGAN NOHUT
28/01/2024	30/01/2024	31/01/2024	01/02/2024	02/02/2024	03/02/2024	04/02/2024
MINESTRONE ÇORBA FİRİN TAVUK (PATATES KAVURMA) KEÇİ SALATA TULUMBA TATLISI	KARAVANBAHAR ÇORBA ET SÖTİ (DOM. PİRİNÇ PILAVI) KARŞIK SALATA CULUSU SARLOT	KEREVİZ ÇORBA TERBİVELİ KÖFTE FES. SOSLU İRADETİ MANDALİNA	SATAK ÇORBA PİLİÇ MEXİKA (DİLİM PATATES) MEVSİM SALATA ELMA	EZOĞELİN ÇORBA KIYMALI YEŞİL MERCİMEK SPANAKLI GÜL BÖREĞİ YOĞURT	ROMEN ÇORBA PİLİÇ BÜYÜK AVDENEZ SALATA BUDENİZ TATLISI	YARMA ÇORBA CİMBİR KAVURMA (PÖRE) KEÇİ SALATA BUDENİZ TATLISI
VEGAN İÇLİ KÖFTE (DOMATES-BİBER)	VEGAN YULPADA MİRCİMEKLI DOLMA	VEGAN TAZE FASULYE	VEGAN FİRİN PATATES	VEGAN YEŞİL MERCİMEK	VEGAN ÇİLİ KÖFTE (DOMATES-BİBER)	VEGAN PIRASA
05/02/2024	06/02/2024	07/02/2024	08/02/2024	09/02/2024	10/02/2024	11/02/2024
BULGUR ÇORBA PİLİÇ STROGANOF BAĞIÇVAN USULU MAKARNA KEÇİ SALATA VEGAN BEZELİYE	YOĞURT ÇORBA KIYMALI TURLU PİRİNÇ PILAVI MANDALİNA VEGAN TURLU	TARHANA ÇORBA MAÇAR GULAS KAŞARLI ERİŞTE AYRAN	EXKSLİ ANADOLU ÇORBA OLIMPİYAT KÖFTE (DİLİM PATATES) AMASRA SALATA HİRA TATLISI	EZOĞELİN ÇORBA KIYMALI İSPANAK (YOĞURT) SU BÖREĞİ ELMA	ALACA ÇORBA PİLİÇ RİCİ (PATATES KAVURMA) AVDENEZ SALATA SUTLAÇ	DOMATES ÇORBA KADINBUDU KÖFTE (PÖRE) KEÇİ SALATA VEGAN BAĞIÇVAN
06/02/2024	06/02/2024	07/02/2024	08/02/2024	09/02/2024	10/02/2024	11/02/2024
KÖYLÜ ÇORBA FİRİN KÖFTE ARPA ŞEHİRİYE PILAVI MUT VEGAN MANTAR SÖTİ	DOMATES ÇORBA SICILYA USULU TAVUK (PÖRE) KIYMALI TURLU MAKARNA VEGAN YULPADA SEBZE DOLMA	MİSİR ÇORBA ET'Lİ TAZE FASULYE BULGUR PILAVI PORTAKAL	DÖĞÜN ÇORBA PİLİÇ TINDIR (SEBZE HAŞLAMA) FETTUÇİNİ ARABATA BAĞIÇVAN SALATA	MAŞ FASULYESİ ÇORBA SUNANLI KÖFTE ARPA ŞEHİRİYE PILAVI MAKARNA VEGAN FİRİN PATATES	ŞEHİRİYE ÇORBA YOĞURTLU KEBAP ZEV. MANTAR MUT	ROMEN ÇORBA ET'Lİ BEZELİYE MİSİR PİRİNÇ PILAVI YOĞURT
13/02/2024	13/02/2024	14/02/2024	15/02/2024	16/02/2024	17/02/2024	18/02/2024
MINESTRONE ÇORBA TAS KEBAB KAŞARLI CEMİZLİ ERİŞTE KEÇİ SALATA VEGAN PIRASA	KEÇİK ÇORBA KIYMALI FİRİN PATATES ARPA ŞEHİRİYE PILAVI YOĞURT VEGAN FİRİN PATATES	MİSİR ÇORBA AÇI USULU TAVUK DOM. PİRİNÇ PILAVI KEÇİ SALATA VEGAN SEBZE KAVURMA (YOĞURT)	TARHANA ÇORBA BELEN KÖFTE (SEBZE HAŞLAMA) BAĞIÇVAN USULU MAKARNA AYRAN	BULGUR ÇORBA KARŞIK MUSAĞA ERİŞTE ELMA	EXKSLİ ANADOLU ÇORBA HİNDİLİ KONIA KEBAP ZEV. KEREVİZ KARAMELİ SARLOT	SEBZE ÇORBA PİLİÇ KAVURMA (DİLİM PATATES) PANCARLI BAĞIÇ SALATA BUDENİZ TATLISI VEGAN BAĞIÇVAN
13/02/2024	13/02/2024	14/02/2024	15/02/2024	16/02/2024	17/02/2024	18/02/2024
AYRANBAŞI ÇORBA KAŞARLI TAVUK (DİLİM PATATES) MEVSİM SALATA GÖNİET VEGAN KARAVANBAHAR	KEREVİZ ÇORBA SAHAN KÖFTE BULGUR PILAVI MUT VEGAN KAKIK MUSAĞA (YOĞURT)	YARMA ÇORBA KIYMALI YEŞİL MERCİMEK PEY. GÜL BÖREĞİ MANDALİNA	LEBENİ ÇORBA ÇİFTLİK KEBAB BULGUR PILAVI CİNDOLU FİRİN TATLISI	KİLİS ÇORBA TATLI EXKSLİ TAVUK (PÖRE) AMASRA SALATA PİRİNÇ KEGÜL	DOMATES ÇORBA ET'Lİ TAZE FASULYE ARPA ŞEHİRİYE PILAVI YOĞURT	ŞAFAK ÇORBA TARHANA KÖFTE PEYNİRLİ MAKARNA MUT
19/02/2024	20/02/2024	21/02/2024	22/02/2024	23/02/2024	24/02/2024	25/02/2024
YOĞURT ÇORBA ET'Lİ KURL FASULYE MİS. PİRİNÇ PILAVI TIRSUJ VEGAN KURL FASULYE	MİSİR ÇORBA MEXİKA KÖFTE (SEBZE HAŞLAMA) BULGUR PILAVI PORTAKAL	YAVLA ÇORBA ET TIRSUJ MEVSİM SALATA HİGHİŞLİ SEKERPANE	MERCİMEK ÇORBA SEBZE TAVUK ARPA ŞEHİRİYE PILAVI AYRAN	AYRANBAŞI ÇORBA KIYMALI TURLU PEY. RULO BÖREK MUT	ROMEN ÇORBA PİLİÇ BÜYÜK KARŞIK SALATA TIRAMISU	BROKOLİ ÇORBA TERBİVELİ KÖFTE FES. SOSLU MAKARNA ELMA
19/02/2024	20/02/2024	21/02/2024	22/02/2024	23/02/2024	24/02/2024	25/02/2024
BROKOLİ ÇORBA ET DÖNER (PÖRE) AVDENEZ SALATA BAL KAKIKLI CEMİZLİ VEGAN LAHANA KAVURMA	MAINTAR ÇORBA TAVUKLU BULGUR KEBAP KAŞARLI ERİŞTE YOĞURT VEGAN TURLU	TARHANA ÇORBA KÖRİ SOSLU KÖFTE SPAGETTİ NAPOLİTEN KARŞIK SALATA VEGAN SEBZE KAVURMA (YOĞURT)	KEÇİK ÇORBA KIYMALI İSPANAK (YOĞURT) FİRİN MAKARNA MANDALİNA	PİDOLİ KÖFTE FİRİN MAKARNA SUTLAÇ	BÖRÜLCE ÇORBA KIBIR KEBAP KAŞARLI CEMİZLİ ERİŞTE PORTAKAL	KİLİS ÇORBA KIYMALI YEŞİL MERCİMEK SU BÖREĞİ YOĞURT
26/02/2024	27/02/2024	28/02/2024	29/02/2024	01/03/2024	02/03/2024	03/03/2024
ŞAFAK ÇORBA YENİBAHARLI HİNDİ KEBAP (LAHANA-DOM. PİRİNÇ PILAVI) AVDENEZ SALATA SUTLU REJANİ VEGAN PIRASA	SEBZE ÇORBA ET'Lİ NOHUT BULGUR PILAVI YOĞURT VEGAN NOHUT	DOMATES ÇORBA FİRİN TAVUK (DİLİM PATATES) MEVSİM SALATA KAZANDIRI	MAINTAR ÇORBA İZMİR KÖFTE ARPA ŞEHİRİYE PILAVI PORTAKAL			
26/02/2024	27/02/2024	28/02/2024	29/02/2024	01/03/2024	02/03/2024	03/03/2024
MİSİR ÇORBA SICILYA USULU TAVUK ERİŞTE MUT VEGAN MANTAR SÖTİ	YARMA ÇORBA KADINBUDU KÖFTE (PÖRE) AMASRA SALATA TULUMBA TATLISI	EXKSLİ ANADOLU ÇORBA KARŞIK SEBZE GRATEN BAĞIÇVAN USULU MAKARNA MANDALİNA	TARHANA ÇORBA ET DÖNER (PİRİNÇ PILAVI) BAĞIÇVAN SALATA MAKARNA VEGAN ÇİLİ KÖFTE (DOMATES-BİBER)			

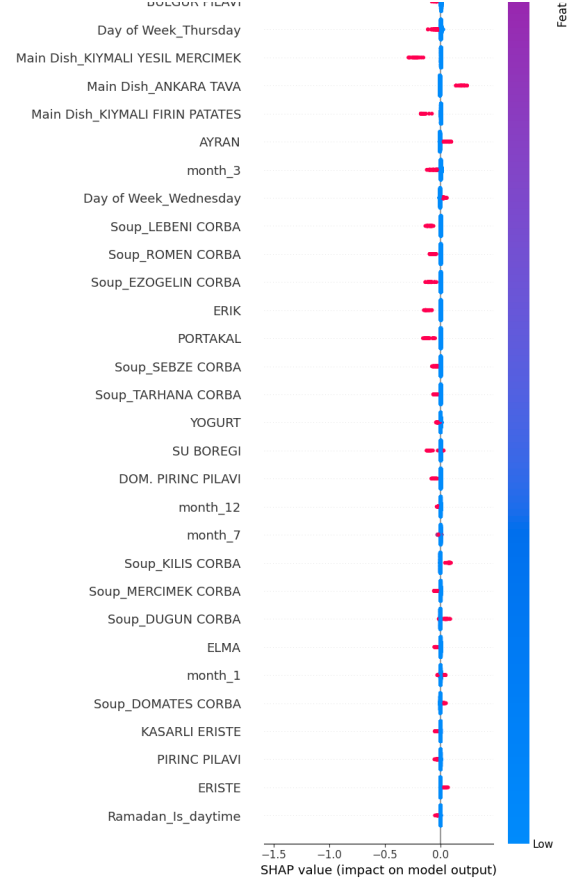
Figure 11: Menu image before processing

MERKEZ - DOĞU KAMPÜS GÜNLÜK SATIŞ BİLGİLERİ												
MARMARA RESTORAN												
TARİH	SABAH KAHVALTI	KAHVALTI TOPLAM	FİX ÖĞLE	KUMANYA ÖĞLE	FİX AKŞAM	KUMANYA AKŞAM	FİKS TOPLAM	SEÇMELİ ÖĞLE	SEÇMELİ AKŞAM	SEÇMELİ TOPLAM	TOPLAM (Ana Yemek)	TOPLAM KUVER
1/1/2024	9	9	182	0	199	0	381	32	216	248	629	638
1/2/2024	28	28	640	3	469	0	1112	78	82	160	1272	1300
1/3/2024	20	20	340	5	531	0	876	273	120	393	1269	1289
1/4/2024	21	21	415	7	202	0	624	107	142	249	873	894
1/5/2024	20	20	406	9	334	0	749	92	33	125	874	894
1/6/2024	10	10	94	0	185	0	279	95	22	117	396	406
1/7/2024	8	8	110	0	120	0	230	19	31	50	280	288
1/8/2024	11	11	153	3	130	1	287	128	27	155	442	453
1/9/2024	4	4	271	2	114	0	387	53	32	85	472	476
1/10/2024	5	5	190	3	59	0	252	58	53	111	363	368
1/11/2024	3	3	116	0	98	0	214	159	17	176	390	393
1/12/2024	8	8	169	5	67	1	242	56	23	79	321	329
1/13/2024	5	5	31	0	35	0	66	20	7	27	93	98
1/14/2024	3	3	37	0	64	2	103	12	6	18	121	124
1/15/2024	2	2	808	3	62	0	873	60	18	78	951	953
1/16/2024	2	2	707	3	119	1	830	84	2	86	916	918
1/17/2024	4	4	765	4	49	0	818	63	38	101	919	923
1/18/2024	4	4	725	0	92	2	819	94	12	106	925	929
1/19/2024	1	1	184	4	76	2	266	41	5	46	312	313
1/20/2024	4	4	34	4	20	0	58	12	17	29	87	91
1/21/2024	3	3	35	0	55	0	90	5	1	6	96	99
1/22/2024	2	2	93	3	116	3	215	112	11	123	338	340
1/23/2024	1	1	169	14	113	0	296	53	9	62	358	359
1/24/2024	9	9	148	8	92	0	248	71	18	89	337	346
1/25/2024	1	1	186	0	124	1	311	97	9	106	417	418
1/26/2024	5	5	150	3	156	0	309	128	17	145	454	459
1/27/2024	2	2	114	0	151	0	265	14	9	23	288	290
1/28/2024	6	6	149	0	155	0	304	10	84	94	398	404
1/29/2024	41	41	1514	1	817	0	2332	215	56	271	2603	2644
1/30/2024	43	43	888	2	661	0	1551	507	93	600	2151	2194
1/31/2024	37	37	1525	29	763	1	2318	97	78	175	2493	2530
TOPLAMLAR	322	322	9	115	6228	14	17705	2845	1288	4133	21838	22160

Figure 12: Sale image before processing



(a) Top features (Part 1)



(b) Top features (Part 2)

Figure 13: SHAP feature importance divided into two parts for readability