



Investigation of Total Debit and Credit Card Spending by Sectors with Different Learning Algorithms

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Abstract

Global economic activity is expanding day by day. On an individual level, people are meeting their needs; furthermore, they are frequently driven by discounts to make unnecessary purchases. Similarly, companies must actively engage in this economic activity and satisfy consumer demands to sustain their commercial operations. Governments are tasked with encouraging this growth while maintaining a balance through savings or precautionary measures. In this context, the usage of debit and credit cards, the cornerstone of modern economic activity, is rapidly increasing. This study aims to use various learning algorithms to classify spending volumes on debit and credit cards in Türkiye. To this end, classification successes will be achieved with the help of learning algorithms, and their results were compared to determining the top performing algorithms. The algorithms used in this study 'Deep learning algorithm', 'Artificial neural network classifier', 'Conjunctive rule algorithm', and 'Alternating Decision tree algorithm'. The performance of these algorithms was evaluated using criteria such as 'True positive rate', 'F-measure', 'Roc area value', 'Kappa statistic', 'Mean absolute error', and 'Root mean square error'. The analysis revealed that the Alternating Decision tree algorithm was the most successful, achieving a classification accuracy of 85.10%.

Keywords: Learning algorithms, Debit card, Credit card, Decision trees

Banka ve Kredi Kartı Toplam Harcamasının Sektörlere Göre Farklı Öğrenme Algoritmaları ile Araştırılması

Öz

Dünya üzerinde ekonomik hareketlilik her geçen gün artmaktadır. Bireysel anlamda insanlar ihtiyaçlarını karşılamakta; bunun yanında ihtiyacı olmasa bile indirim etiketi üzerinden harcama yapmaktadır. Firmalarda benzer şekilde ticaretlerini devam ettirebilmek adına bu ekonomik hareketliliğe katılmak ve insanların ihtiyaçlarını karşılamak zorundadır. Ülkeler bu durumu teşvik ederek, tasarruf yaparak ya da tedbir alarak dengede tutmakla yükümlüdür. Bu bağlamda ekonomik hareketliliğin en önemli noktası olan banka ve kredi kartlarının kullanım yoğunluğu ve ekonomik hareketlilikteki payı hızla yükselmektedir. Bu çalışmada, Türkiye'deki banka ve kredi kartlarının harcama tutarlarının sınıflandırılmasında bazı öğrenme algoritmalarının kullanılması amaçlanmaktadır. Bu doğrultuda öğrenme algoritmaları yardımıyla sınıflandırma başarıları elde edilecek ve sonuçlar karşılaştırılarak hangi algoritmanın en başarılı sınıflandırma performansı gösterdiği belirlenecektir. Çalışmada öğrenme algoritmalarından 'Derin öğrenme algoritması', 'Yapay sinir ağıları sınıflandırıcısı', 'Birleşik kural algoritması' ve 'Değişmeli karar ağaçları algoritması' kullanılmıştır. Algoritmaların performanslarını incelemek için ise kullanılan sınıflandırma performans kriterleri sırasıyla: 'Doğru pozitif oranı', 'F-ölçütü', 'Roc değeri', 'kappa istatistiği', 'ortalama mutlak hata' ve 'Kök ortalama hata kare' dir. Yapılan analizler sonucunda %85,10 ile Değişmeli karar ağaçları algoritması en başarılı sınıflandırma algoritması olarak belirlenmiştir.

Anahtar Kelimeler: Öğrenme algoritmaları, Banka kartı, Kredi kartı, Karar ağaçları

1. Introduction

With the evolving economic order in the world, different economic variables are emerging constantly. From an economic perspective, these developments must be closely monitored by nations. Taking measures in response to ongoing global shifts and ensuring economic balance within the system are among the primary responsibilities of countries. This is essential for nations to enhance their level of development. Most economies are affected by global developments and are navigating difficult times. On the other hand, economic activity has become more dynamic over time. Individuals drive economic activity by meeting their needs. Companies play a leading role in economic vitality through exports and imports. Countries provide support to individuals and companies in the context of these developments. Increasing the purchasing power of citizens is one of the main objectives of countries. In addition, countries provide incentives to companies by offering concessions in certain situations.

The most critical factor for economic activity is ensuring economic freedom. Individuals satisfy their needs through their purchasing power. They conduct purchases using cash or cards. It is well established that they're prior to the rise of the internet, when physical shopping was the norm and online ordering was not prevalent, cash was the primary medium of exchange. In recent years, the frequency of debit and credit card usage, which surged especially during the Covid-19 pandemic, persists today. It has been observed that online shopping increased significantly during the pandemic, as people were subject to mobility restrictions and spent most of their time at home. It is an undeniable fact that debit or credit cards provide users with a sense of security. Since carrying large amounts of cash is cumbersome, conducting transactions with cards has become standard practice. Significant advantages of card usage include the ability to block the card in case of loss through formal channels, thereby ensuring the safety of one's funds. Additionally, the ability to make installment-based purchases with cards incentivizes consumers to use them. Addressing urgent cash needs is also a key factor. In this context, the significant increase in debit and credit card usage in recent years has resulted in the accumulation of massive datasets. Determining the patterns and volume of card usage is a significant issue that requires careful consideration. The most suitable methods for analyzing such extensive datasets are learning algorithms. Through these algorithms, different analyses such as classification and prediction are performed, yielding highly accurate results.

In light of this information, the existing literature reveals numerous studies employing diverse methodologies regarding debit and credit cards. Wright (2003) developed a model of a debit or credit card payment system and investigated the determination of the most socially appropriate fee structure between charges applied to cardholders and merchants. Scholnick et al. (2008)

presented a critical review of the extensive body of literature on debit/credit cards and ATMs. Borzekowski et al. (2008) examined the contemporary use of debit cards by US consumers based on demographic characteristics derived from a new nationally representative consumer survey. Yilmazkuday and Yazgan (2009) analyzed the effects of credit and debit cards on money in circulation using a forecasting method. The study demonstrated that the effect of debit card usage on money demand was more significant than that of credit card usage. Zinman (2009) conducted a study on debit and credit card preferences. He is revealing that debit cards have become a stronger alternative to credit cards over time. Foscht et al. (2010) aimed to investigate the link between payment method preference and customer satisfaction. They examined the Austrian market and the effect of debit/credit card preference and usage on customer satisfaction and loyalty. Kim and Lee (2010) employed the search theory model to explain both the rapid growth in debit card usage over time and the cross-sectional variation in its adoption. David et al. (2016) used micro-level data to compare cash holding and cash usage, focusing on the two primary services debit cards offer consumers: cash withdrawal and payment. Putra et al. (2021) utilized a vector error correction model to investigate the effect of payment instruments represented by both debit cards and credit cards on the velocity of money in Indonesia between January 2016 and June 2020. The study concluded that card-based payment instruments have a significant impact on money circulation in Indonesia in the long term. Anong and Routh (2022) aimed to examine the relationship between prepaid debit card usage and the intention to open a bank account within a twelve-month period. Ma'rifah and Faridatussalam (2023) examined the effect of nominal debit card transactions, nominal credit card transactions, and nominal electronic money transactions on the money supply level between 2013 and 2022. The study concluded that the amount of money in circulation was simultaneously affected by nominal debit card, credit card, and electronic money transactions, both before and after Covid-19 pandemic. Alashwali et al. (2024) conducted a survey involving 150 participants who were victims of debit/credit card fraud in the US; their findings indicated that significantly more participants were affected psychologically rather than financially. Huse et al. (2025) investigated the predictive modeling of credit card payment delays by utilizing credit and debit card data simultaneously.

There are also studies in literature that employ learning methods in the context of debit and credit cards. Davis et al. (1992) utilized various learning algorithms for credit card evaluation. They demonstrated the suitability of applying machine learning algorithms to credit card evaluation and compared the performance of these algorithms. Puh and Brkić (2019) examined the performance of three learning algorithms to detect fraud in real-world data involving credit card transactions. Dornadula and Geetha (2019) analyzed customers' past transaction history and developed a new fraud detection

method to identify behavioral patterns. Sadineni (2020) employed several machine learning algorithms such as Artificial Neural Networks, Decision Trees, Support Vector Machines, Logistic Regression, and Random Forests to detect fraudulent credit card transactions. Khatri et al. (2020) presented comparisons of several learning algorithms to distinguish between legitimate and fraudulent card transactions. Alarfaj et al. (2022) utilized several machine learning algorithms, including the Extreme Learning Machine, Decision Tree, Random Forest, Support Vector Machine, Logistic Regression, and XG Boost for credit card fraud detection. Afriyie et al. (2023) examined the performance of three different machine learning algorithms for classifying, predicting, and detecting fraudulent credit card transactions. By comparing the performance of these algorithms, they demonstrated that the random forest model achieved a maximum accuracy of 96% in identifying fraudulent transactions. Wahab et al. (2024) evaluated the effectiveness of a deep learning algorithm for predicting credit card defaults and compared it with other machine learning algorithms such as Decision Tree and Adaboost. Agrawal et al. (2025) employed machine learning algorithms to analyze credit card spending patterns and develop reward programs aligned with strategic objectives. As a result of their study, they proposed strategies to optimize credit card reward programs by aligning rewards with high margin spending categories and leveraging adaptive frameworks.

Debit and credit cards are ubiquitous in daily life. In this context, challenges related to the use of debit and credit cards have become increasingly prominent. It is possible to encounter various inquiries regarding the utilization of these products, the transaction volumes, and the specific sectors in which they are employed. This study focuses on the total spending amounts via debit and credit cards in Türkiye. The analysis is detailed by examining the sectors in which these cards are used. The main objective of the study is to classify the total spending amounts of debit and credit cards using different learning algorithms and to determine which algorithm yields the most successful result. For this purpose, various classification performance criteria will be employed. In addition, performance differences will be visually presented using Roc curves.

While the existing literature extensively covers payment systems, money circulation, and credit card fraud detection using machine learning, a clear empirical gap remains regarding how sectoral expenditure variations directly drive aggregate card spending patterns in emerging economies. Specifically, there is limited research evaluating the comparative classification performance of diverse learning algorithms ranging from rule-based models to deep learning structures on sector specific post-pandemic transaction data in Türkiye. This study fills this gap by utilizing high-frequency weekly sector-level data to evaluate and contrast the classification capabilities of distinct algorithm families, thereby offering policymakers and financial sector

practitioners a data-driven framework to monitor consumer spending behaviors and economic vitality.

2. Materials And Method

2.1. Data set

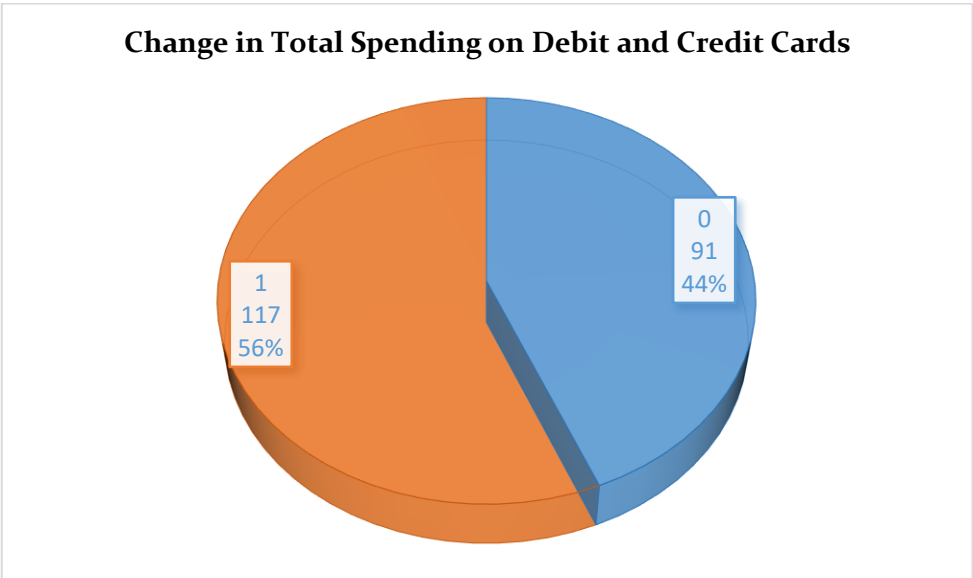
The study focuses on the total amount spent using debit and credit cards in Türkiye. In this regard, the selection and accuracy of the dataset are crucial. This is because determining expenditure concentration across various sectors is an important consideration. In this context, data were obtained from the Central Bank of the Republic of Türkiye (CBRT) electronic data delivery system (CBRT Web Page). The dataset covers the post Covid-19 pandemic period. Specifically ranging from 01.01.2022 to 26.12.2025. This data is published weekly and reflects percentage changes compared to the previous period. A total of 208 weekly observations are available. In the study, the variable ‘Total spending on debit and credit cards’, was selected as the dependent variable, while the remaining 28 variables were utilized as independent variables. The variables employed in the study are detailed in Table 1. Furthermore, the dependent variable ‘Total spending on debit and credit cards’ was binarized: it is coded as ‘0’ to represent a decrease compared to the previous period and ‘1’ to represent an increase. Figure 1 illustrates the distribution of these binary outcomes in the study.

Table 1. Variables used in this study

<i>Variables Name (Percentage change)</i>	<i>Variables Type</i>
Car Rental	Independent variables
Vehicle Rental_Sales/Service/Spare Parts	
Gasoline and Fuel Stations	
Various Food Products	
Direct Marketing	
Education / Stationery / Office Supplies	
Electrical_Electronic Goods, Computers	
Clothing and Accessories	
Airlines	
Service Sectors	
Accommodation	
Clubs / Associations / Social Services	
Casinos / Bars	
Jewelry Stores	
Markets and Shopping Centers	
Furniture and Decoration	
Contractor Services	
Health/Health Products/Cosmetics	
Travel Agencies/Transportation	
Insurance	
Telecommunications	
Construction Materials, Hardware, Nails	
Food	
Public/Tax Payments	

Individual Retirement	
Online Shopping	
Purchases Made by Mail/Phone	
Customs Duty Payments	
Total spending on debit and credit cards	Dependent Variable

Figure 1. Display of the number and percentage change in total spending with bank and credit cards



The model architecture is specifically structured for contemporaneous classification, utilizing sectoral changes at week t to classify aggregate spending shifts at the same period t . It does not incorporate lagged predictors ($t - 1$) for forward-looking time-series forecasting.

2.2. Algorithms

The study focuses on the total expenditure using debit and credit cards in Türkiye. Accordingly, the total spending amounts via these cards will be classified by sector. Different learning algorithms will be employed for classification. Based on the existing literature, these algorithms have been identified as ‘Deep Learning Algorithms’, ‘Artificial neural network classifier’, ‘Conjunctive Rules Learning Algorithms’, and ‘Alternating Decision Tree Algorithms’ based on the literature. In addition, various Classification Performance Criteria will be utilized to measure the classification performance of these algorithms. These criteria are defined as ‘True Positive (TP) Rate’, ‘F-measure’, ‘Receiver Operating Characteristic (Roc) Area Value’, ‘Kappa (κ) statistic’, ‘Mean Absolute Error (Mae)’, and ‘Root Mean Square Error (Rmse)’. A k-fold cross-validation method

was applied in the study. The k value was selected as 10, a parameter frequently cited in the literature (Breiman et al., 1984; Filiz, 2023). Model performance was evaluated using standard classification metrics provided by WEKA, including TP Rate, F-Measure, ROC Area, κ statistic, MAE, and RMSE. The overall summary values reported in the comparative tables denote the software-generated class-weighted averages across both outcomes (1 and 0). In addition, single positive-class (1) TP Rate values are explicitly reported in the text to demonstrate directional classification accuracy.

To handle the weekly indexed data appropriately without introducing look-ahead bias or data leakage, the continuous metrics were transformed into stationary percentage changes representing period-to-period directional fluctuations (0 for decrease, 1 for increase). Furthermore, rather than employing random data splitting, a non-shuffled, temporally sequential 10-fold cross-validation scheme was adopted. The hyperparameters of the algorithms are given in Table 2.

Table 2. Hyperparameters of the algorithms

	<i>DL</i>	<i>MLP Classifier</i>	<i>Conjunctive Rule</i>	<i>AD Tree</i>
<i>Number of epochs</i>	10	-	-	-
<i>Attribute Normalization</i>	Standardize	-	-	-
<i>Set the cache mode</i>	Memory	-	-	-
<i>Data queue size</i>	0	-	-	-
<i>Resume</i>	False	-	-	False
<i>Preserve filesystem cache</i>	False	-	-	-
<i>Number of GPUs</i>	1	-	-	-
<i>Size of prefetch buffer for multiple GPUs</i>	24	-	-	-
<i>Model parameter averaging frequency</i>	10	-	-	-
<i>Batch size</i>	100	100	100	100
<i>Debug</i>	False	False	False	False
<i>Do not check capabilities</i>	False	False	False	False
<i>Num decimal places</i>	2	2	2	2
<i>Num functions</i>	-	2	-	-
<i>Num threads</i>	-	1	-	-
<i>Pool size</i>	-	1	-	-
<i>Ridge</i>	-	0.01	-	-
<i>Seed</i>	-	1	1	1
<i>Tolerance</i>	-	1.0e-6	-	-
<i>Use CGD</i>	-	False	-	-
<i>Exclusive</i>	-	-	False	-
<i>Folds</i>	-	-	3	-
<i>Min no.</i>	-	-	2.0	-

<i>Num antds</i>	-	-	-1	-
<i>Num of boosting iterations</i>	-	-	-	10
<i>Save instance data</i>	-	-	-	False

Structurally, a clear distinction was maintained between the Multi-Layer Perceptron (MLP) and Deep Learning (DL) classifiers: the MLP model utilizes a conventional shallow feedforward network architecture optimized via second-order BFGS algorithms, whereas the DL framework incorporates a deeper multi-layered network topology enhanced with modern activation functions and dropout regularization to model complex feature interactions.

2.2.1. Deep Learning Algorithms

The first learning algorithm employed for the purposes of this study is Deep Learning (DL). This algorithm has been widely adopted in recent years, demonstrating superior performance in developing classification and prediction models. It performs classification and regression tasks using multi-layer perceptron. Design to mimic the neural structure of human brain. DL can perform complex analyses on datasets ranging from structured metadata to high-dimensional spatial images through iterative processing (WekaDeeplearning4j Web Page). This algorithm has significantly advanced the state of the art in numerous fields such as speech regognition, visual object recognition, object detection, and drug discovery. In addition, it facilities different approaches in multimedia domains such as video, image, photo, and speech processing. This algorithm was selected due to its prevalence in the literature (LeCun et al. 2015, Shinde and Shah, 2018; Fu et al. 2022; Mehrish et al. 2023; Sharifani & Amini, 2023; Chen et al. 2025).

2.2.2. Artificial Neural Network Classifier (Multilayer Perceptron Classifier) Machine Learning Algorithms

In line with the objective of the study, the second learning algorithm to be utilized for classifying the total expenditure of debit and credit cards is the Multilayer Perceptron (MLP) Classifier Machine Learning Algorithm. Widely employed since its inception, this algorithm consistently produces successful results in classification and forecasting problems. Generally, utilizing the optimization class, it trains a multilayer perceptron, typically with a single hidden layer, by minimizing the specified loss function along with a second-order penalty applied via the BFGS (Broyden, Fletcher, Goldfarb, and Shanno) method. To ensure computational efficiency and accuracy, it incorporates different transformation methods in the input and output layers. This algorithm has also been widely cited in the literature across various domains (Murtagh, 1991; Morariu et al., 2017; Al Bataineh et al., 2022; Sharma et al., 2022; Ahmed et al., 2023).

2.2.3. Conjunctive Rule Learning Algorithms

The third learning algorithm employed to classify the total spending amounts of debit and credit cards for the purpose of this study is the rule-based Conjunctive Rule (CR) Learning Algorithm. As with other algorithms in the rule-based category, it achieves high-performance results in classification and prediction. In general, it formulates a rule by creating a class value combined via the logical 'AND' operator for classification or regression. In this framework, the result reflects the distribution of existing classes within the dataset. This algorithm calculates the Information Gain for each attribute. It selects a representative class and constructs a rule by applying either Reduced Error Pruning or simple pre-pruning depending on the number of categories. Ultimately, it aims to derive a comprehensive rule. Various studies utilizing this algorithm have been examined in the literature (Keller and Tahani, 1992; Ughetto et al., 1999; Van Zyl and Cloete, 2004; Fürnkranz & Kliegr, 2015; Wang et al., 2022).

2.2.4. Alternating Decision Tree Algorithms

In line with the objective of the study, the fourth and final algorithm employed for the classification of debit and credit card spending amounts is the Alternating Decision Tree (AD Tree) Algorithm. Like other learning algorithms, this is a decision tree-based approach utilized for classification and prediction. Its fundamental principle is to construct an alternative decision tree structure. This algorithm is frequently applied to binary classification problems and offers a more flexible and interpretable structure compared to traditional decision trees. In this context, it is highly preferred and yields successful results. Further literature shows that this algorithm has been effectively used in various classification and prediction tasks (Freund and Mason, 1999; Holmes et. al. 2002; De Comité et. al. 2003; Jabbar et. al. 2014; Venkatesan and Velmurugan, 2015).

2.2.5. Classification Performance Criteria

In line with the objective of the study, various learning algorithms will be utilized to classify the total volume of debit and credit card spending. Classification performance criteria will be employed to investigate efficacy of these algorithms. As is common in literature, criteria such as 'True Positive (TP) Rate', 'F-measure', 'Receiver Operating Characteristic (ROC) Area Value', 'Kappa (κ) statistic', 'Mean Absolute Error (Mae)', and 'Root Mean Square Error (Rmse)' will be applied. The TP Rate, also known as sensitivity or recall, measures the proportion of real positives that are correctly identified. This is the first criteria to be examined. The closer this value is to 1, the higher the classification accuracy of the algorithm. Similarly, the F-measure is calculated based on precision and recall and is ideally close to 1. The Roc Area value

represents the area under the performance curve. A larger area under this curve indicates a more successful classification performance by the algorithm. Consequently, the Roc Area value is expected to be close to 1. Similarly, the κ statistic value is also anticipated to be close to 1, representing a high degree of agreement between classified and real classes. The Mae and Rmse values represent the error rates of the models. Therefore, these criteria are ideally close to 0. In general, these criteria collectively support the findings of the TP Rate.

In binary classification tasks, evaluating categorical precision alone may overlook the confidence and calibration of classification probabilities. While metrics such as TP Rate, F-measure, Kappa, and ROC Area capture class discriminability and balance, MAE and RMSE are additionally incorporated to quantify the continuous error magnitude between estimated class probabilities and actual binary target labels (0 or 1). Assessing both categorical performance and probabilistic error metrics ensures a robust and comprehensive evaluation of model stability and accuracy.

3. Application

In accordance with this research objectives, the classification of debit and credit card expenditure volumes in Türkiye was performed using selected learning algorithms. The efficacy of these algorithms was evaluated based on established classification performance criteria. To provide a systematic analysis, the application stage was structured into five distinct stages as outlined below:

- * In the first stage, calculation of the descriptive statistics for the independent variables included in the study.
- * In the second stage, determination of the classification performance of the learning algorithms using the defined performance criteria.
- * In the third stage, evaluation of the correctly classified instances for each learning algorithm.
- * In the fourth stage, visualization and analysis of the Roc Area curves for the respective learning algorithms.
- * In the fifth stage, comparison of the classification sensitivities across the evaluated learning algorithms to identify the most robust model.

4. Findings

In accordance with the research objectives and the previously outlined application framework, various machine learning algorithms were employed

to classify debit and credit card expenditure volumes in Türkiye. The analytical process was conducted in five distinct stages.

Pursuant to the first stage of the analysis, the descriptive statistics of the independent variables were calculated. These statistical measures, providing an overview of the dataset's characteristics, are presented in Table 3.

Table 3. Basic statistical values of the independent variables used in the study

<i>Variables Name</i>	<i>Maximum</i>	<i>Minimum</i>	<i>Average</i>	<i>Standart deviation</i>	<i>Range of Variation</i>
<i>Car Rental</i>	28,98	-28,02	1,75	9,06	57
<i>Vehicle Rental_Sales/Service/Spare Parts</i>	164,40	-63,56	3,26	22,20	227,96
<i>Gasoline and Fuel Stations</i>	33,79	-27,09	1,70	10,24	60,88
<i>Various Food Products</i>	40,72	-33,29	1,49	7,89	74,01
<i>Direct Marketing</i>	87,33	-54,94	2,56	18,90	142,27
<i>Education / Stationery / Office Supplies</i>	163,65	-63,86	5,50	32,41	227,51
<i>Electrical_Electronic Goods, Computers</i>	67,32	-38,09	2,20	15,44	105,41
<i>Clothing and Accessories</i>	56,30	-50,21	2,03	13,15	106,51
<i>Airlines</i>	57,53	-19,52	1,24	8,34	77,05
<i>Service Sectors</i>	84,81	-44,66	2,29	15,76	129,47
<i>Accommodation</i>	58,93	-29,34	1,76	11,56	88,27
<i>Clubs / Associations / Social Services</i>	111,69	-75,60	4,00	23,63	187,29
<i>Casinos / Bars</i>	101,02	-60,59	2,61	17,35	161,61
<i>Jewelry Stores</i>	76,66	-52,76	2,75	16,73	129,42
<i>Markets and Shopping Centers</i>	38,63	-34,41	1,49	7,10	73,04
<i>Furniture and Decoration</i>	77,52	-47,36	2,36	15,28	124,88
<i>Contractor Services</i>	197,92	-68,79	4,26	27,16	266,71
<i>Health/Health Products/Cosmetics</i>	107,65	-45,81	2,25	15,28	153,46
<i>Travel Agencies/Transportation</i>	34,03	-26,32	1,58	8,61	60,35
<i>Insurance</i>	142,92	-63,74	3,42	21,54	206,66
<i>Telecommunications</i>	84,54	-40,47	2,32	16,66	125,01
<i>Construction Materials, Hardware, Nails</i>	198,73	-71,32	3,69	25,57	270,05
<i>Food</i>	25,60	-32,01	1,52	6,76	57,61
<i>Public/Tax Payments</i>	666,40	-79,43	23,22	80,96	745,83
<i>Individual Retirement</i>	75,14	-33,70	2,72	18,92	108,84
<i>Online Shopping</i>	109,13	-45,82	2,85	18,34	154,95
<i>Purchases Made by Mail/Phone</i>	91,38	-50,75	2,39	16,88	142,13
<i>Customs Duty Payments</i>	1130,36	-92,70	44,32	134,98	1223,06

According to Table 3, the 'Customs Duty Payments' variable exhibits the most prominent values across all descriptive statistical metrics. Similarly, the 'Public/Tax Payments' variable demonstrated a distribution pattern comparable to this variable.

Following the descriptive analysis, in line with the second phase of the study, the classification performance of the learning algorithms was evaluated using various performance criteria. These results are presented in Table 4.

Table 4. Classification performance of learning algorithms

	<i>DL</i>	<i>MLP Classifier</i>	<i>Conjunctive Rule</i>	<i>AD Tree</i>
<i>TP Rate</i>	79,30%	82,20%	78,80%	85,10%
<i>F-measure</i>	0,7930	0,8210	0,7840	0,8500
<i>Roc Area</i>	0,8750	0,9022	0,7818	0,9140
<i>κ statistic</i>	0,5795	0,6355	0,5594	0,6938
<i>Mae</i>	0,2832	0,1961	0,3017	0,2200
<i>Rmse</i>	0,3727	0,3676	0,4110	0,3280

* Reported overall metrics (TP Rate, F-Measure, ROC Area, Kappa, MAE, RMSE) represent software-generated Weighted Averages across both classes (1 and 0). For instance, in the ADTree model, the specific positive-class (1) TP Rate is 90.6%, whereas the weighted average TP Rate across both classes is 85.1%.

According to Table 4, the Alternating Decision Tree (ADTree) algorithm demonstrated superior classification performance, achieving an accuracy of 85.10%. This robust result is further validated by the F-measure (0.8500), Roc Area (0.9140), κ statistic (0.6938), and a lower Rmse (0.3280). The Multilayer Perceptron (MLP) Classifier was identified as the second-best performing model, yielding an accuracy of 82.20%. Its performance is corroborated by an F-measure of 0.8210, Roc Area of 0.9022, κ statistic of 0.6355, Mae of 0.1961, and Rmse of 0.3676. In contrast, the lowest classification efficacy was observed in the Conjunctive Rule algorithm, which achieved 78.80% accuracy. This lower performance is consistent with its criteria, including an F-measure of 0.7840, Roc Area of 0.7818, κ statistic of 0.5594, Mae of 0.3017, and Rmse of 0.4110.

Following this comparative analysis, the third stage of the study quantified the instances of correctly classified data, as detailed in Table 5.

Table 5. The number of successful classifications by learning algorithms

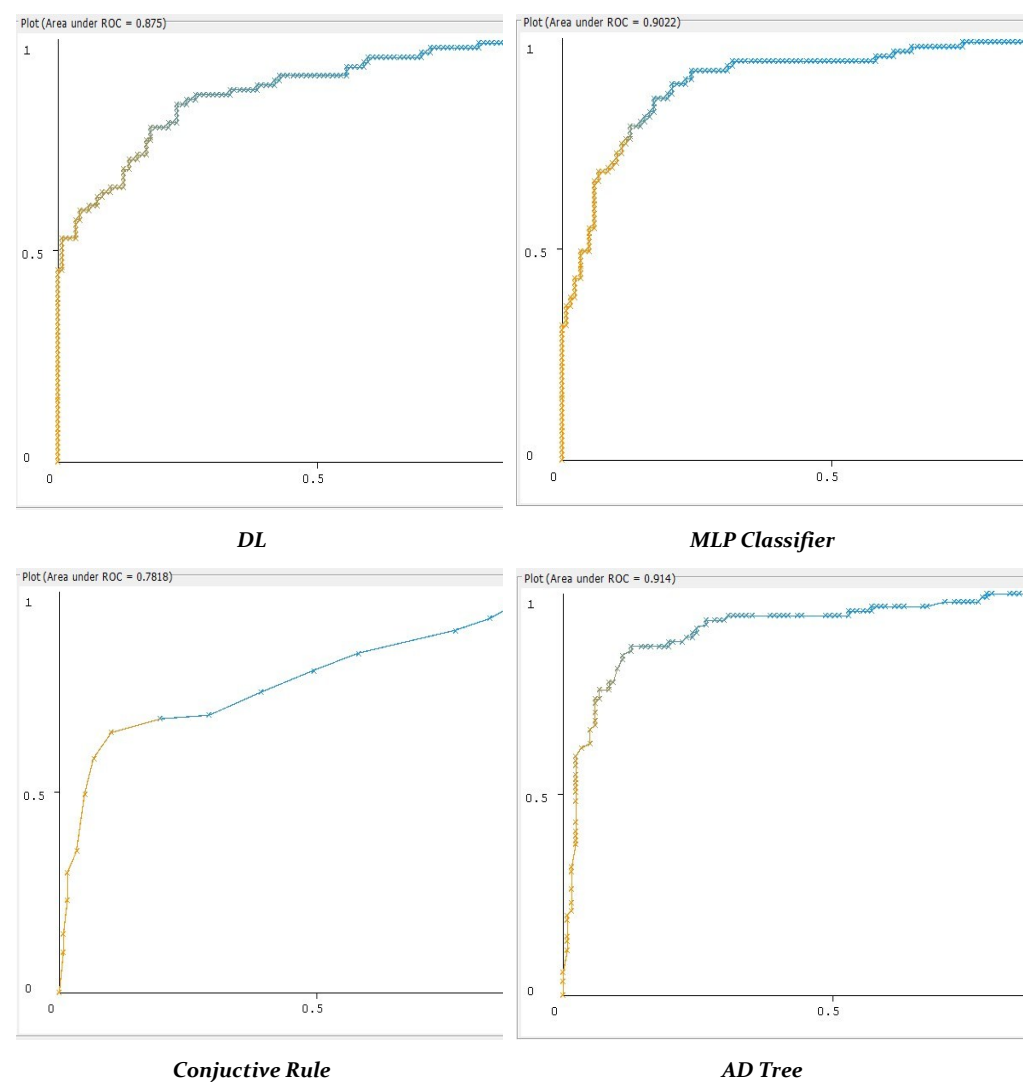
	<i>DL</i>		<i>MLP Classifier</i>		<i>Conjunctive Rule</i>		<i>AD Tree</i>	
	0	1	0	1	0	1	0	1
0	69	22	69	22	59	32	71	20
1	21	96	15	102	12	105	11	106

According to Table 5, the ADTree algorithm outperformed the other models in terms of correctly classified instances, successfully identifying 177 out of 208 observations (71 true negatives and 106 true positives). The MLP Classifier followed in second place with 171 successful classifications (69 + 102). The Deep

Learning algorithm ranked third, correctly identifying 165 instances (69 + 96), while the Conjunctive Rule algorithm yielded the lowest frequency of correct classifications with a total of 164 (59 + 105).

Pursuant to the fourth phase of the study, the classify discriminability of the learning algorithms was visualized using Roc Area curves, as illustrated in Figure 2.

Figure 2. Display of Roc Area curves of learning algorithms



As illustrated in Figure 2, the ADTree algorithm, previously identified as the most effective classification model, also yielded the optimal result for the Roc Area (0.9140). This was followed by the MLP Classifier, which achieved the

second-highest area under the curve (0.9022). These findings confirm that the ADTree model maintains a high degree of discriminative power in classifying spending patterns.

Finally, in the fifth stage of the study, the classification sensitivities (TP Rate) of the learning algorithms were compared, as visually represented in Figure 3.

Figure 3. Comparison of classification success rates (TP rate) of learning algorithms

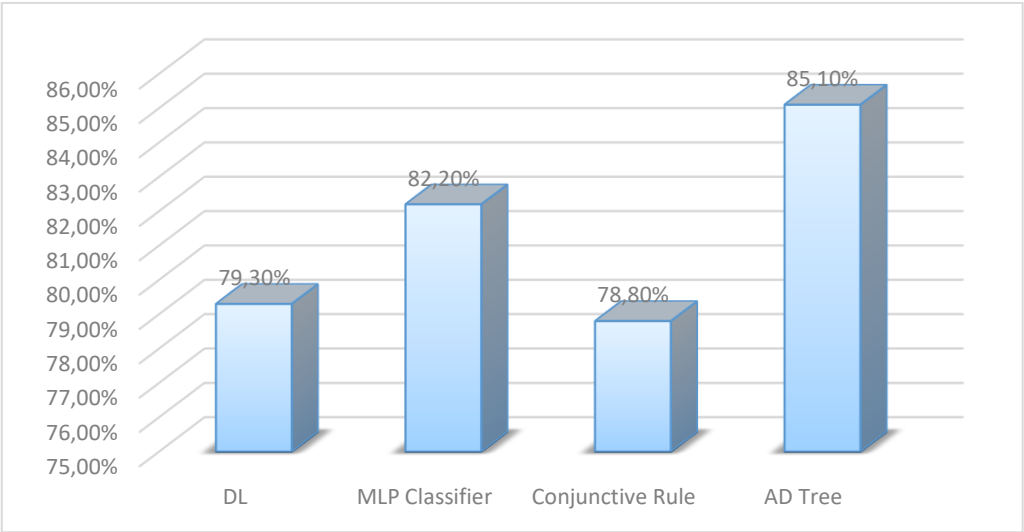


Figure 3 illustrates a comparative analysis of the classification performance of the evaluated algorithms based on the TP Rate. This visualization highlights the sensitivity of each model, providing a clear indication of their respective abilities to correctly identify positive instances within the dataset.

Note on Variable Distributions: The substantial variation and maximum values observed in 'Public/Tax Payments' and 'Customs Duty Payments' stem from period-specific fiscal regulations, structured tax restructuring packages, and exchange rate volatility in Türkiye. These macro-fiscal transactions occur in concentrated, high-volume cycles, presenting distinct statistical profiles compared to continuous retail spending categories. Rather than excluding these attributes through feature reduction which would alter the comprehensive empirical footprint of the payment ecosystem the full sectoral feature set was preserved to rigorously test the classification robustness of each learning algorithm under high-variance conditions.

It should be noted that the analytical framework of this study is intentionally structured around a holistic algorithmic benchmarking evaluation rather than model-based feature importance ranking or causal attribution. Retaining the complete, unmanipulated sectoral variable space without prior feature selection or post-hoc permutation weighting allows for an unbiased assessment of how distinct machine learning families handle high-

dimensional, intercorrelated sectoral transaction data. While certain fiscal and macro-level indicators (such as Public/Tax and Customs Duty Payments) exhibit prominent variance due to policy-driven lump-sum periods, the current models prioritize multi-sectoral pattern recognition over isolated feature contribution. Explicitly quantifying feature importance metrics and examining individual variable sensitivity are intentionally left as primary avenues for future research focusing on causal feature attribution.

5. Discussion and Conclusion

Comprehensive analyses were conducted in accordance with the study's objectives and methodological framework, yielding significant empirical results. A suite of learning algorithms was deployed to classify debit and credit card expenditure volumes in Türkiye. To rigorously evaluate the classification accuracy of these algorithms, multiple classification performance criteria were utilized. Furthermore, comparative visualizations of TP Rate values and Roc Area curves were provided to illustrate the models' discriminative power. The learning algorithms employed in this study were strategically selected from diverse categories within the machine learning literature, ensuring a robust cross-disciplinary evaluation.

In today's dynamic economic landscape, analyzing debit and credit card expenditure patterns plays a pivotal role in shaping financial contemporaneous classification. Monthly reviews of transaction data provide critical insights into sector-specific spending behaviors. Consequently, monitoring these expenditure volumes is essential for maintaining a healthy balance between income and expenses. This study addressed this issue by employing various machine learning algorithms to classify card spending amounts in Türkiye. The evaluated algorithms generally demonstrated classification accuracy ranging from 79% to 85%. Among the models tested, the ADTree algorithm emerged as the most robust classifier algorithm. These findings are consistent with previous literature that highlights the efficacy of the ADTree algorithm in complex classification tasks (Liu et al., 2005; Nguyen, 2016). In this study, various performance metrics were employed to rigorously evaluate the classification efficacy of the selected learning algorithms. The TP Rate was prioritized as the primary metric, a decision corroborated by the literature, which emphasizes its significance in assessing model sensitivity (Obi, 2023; Mohammadi et al., 2023). Furthermore, the Roc Area was utilized to evaluate the discriminative ability of the algorithms. The resulting Roc curves provided a visual validation of the algorithms' classification success, reinforcing the premise that the Roc Area is a critical determinant of model performance. This approach aligns with established studies highlighting the diagnostic importance of this metric (Kumar and Indrayan, 2011; Jaskowiak et al., 2022). Overall, the empirical results of this study are strongly supported by

existing literature, demonstrating the reliability and consistency of the findings. Consequently, this study serves as an essential guide for households, economists, and policy makers in managing financial stability and understanding consumer behavior.

Despite its contributions, this study has certain limitations that should be acknowledged. First, the research was conducted exclusively within the geographical and economic context of Türkiye. Second, the dataset comprises weekly observations of debit and credit card expenditure volumes, covering the period from January 1, 2022, to December 26, 2025. Furthermore, the scope of the comparative analysis was limited to the classification accuracies obtained from four specific models: Deep Learning, Multilayer Perceptron Classifier, Conjunctive Rule, and Alternating Decision Tree. Finally, the evaluation of these algorithms was restricted to the following performance metrics: TP Rate, F-measure, Roc Area, κ statistic, Mae, and Rmse. These parameters define the boundary of the current analysis and provide a baseline for future comparative research. Furthermore, considering the ratio of 28 sectoral independent variables to 208 weekly observations, potential overfitting risks were effectively controlled and mitigated using structural algorithmic regularization (such as tree pruning rules and restricted network topologies) alongside non-shuffled 10-fold cross-validation. The transformation of raw metrics into stationary percentage changes constrained the variance of the input space. Additionally, the integration of structural regularization techniques such as tree pruning in ADTree, penalty optimization in MLP, and dropout layers in Deep Learning combined with strict 10-fold cross-validation, effectively prevented model memorization. The close alignment between classification accuracy, Kappa values, and error bounds across validation folds empirically verifies that the models maintained robust generalization capabilities despite the moderate sample size.

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