

Research Article

Received: date:09.05.2026
Accepted: date: 17.06.2026
Published: date:30.06.2026

Examining the Performance of Machine Learning Algorithms in Estimating the Unemployment Rate

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Abstract: Unemployment affects the whole country deeply. It is more than a personal struggle. This rate serves as a key sign of economic health. Governments focus on this issue closely. Low unemployment means the economy works well. It supports a better life for everyone. Many countries offer help to create new jobs. This research predicts future unemployment in Türkiye. It applies RBF Regression, SVM Regression, and Random Forest methods. The study examines data between 2005 and 2025. It tests each algorithm against the others. SVM Regression stands out among them. It reaches a high accuracy of 91%. The study also uses the ReliefF algorithm to pick important factors. Industry and construction sectors matter the most. Employment and labor force participation rates follow them. The results stay strong even with fewer variables. This proves that a simple model works effectively. Successful forecasting requires only the most relevant data.

Keywords: Unemployment rate, Estimation, Machine learning, Feature selection

1. Introduction

Unemployment is a multidimensional phenomenon that directly impacts not only individual welfare but also national economic stability and sustainable development. Anticipating dynamics in the labor market is critical for both individual career planning and strategic interventions by policymakers. Although numerous studies in literature focus on unemployment forecasting, there is a clear need for further research analyzing the unique dynamics of emerging markets through machine learning algorithms. This study aims to fill this gap in the literature by analyzing unemployment trends in the Turkish economy using a data-driven approach.

Unemployment impacts the nation as a whole and goes beyond a personal struggle. Every country has a duty to create new jobs. Governments provide safe and peaceful work environments. Good employment strengthens the national economy directly. Countries support many sectors through careful planning. Tourism creates seasonal work via special incentives. The agricultural sector follows a similar path. Industry, sports, and services offer new roles for individuals. These steps increase the general welfare of the public. People find jobs they truly enjoy. The national unemployment rate drops as a result. Researchers use data analysis to understand these trends. Data sets grow larger every day. Standard analysis becomes more difficult over time. Popular machine learning algorithms solve this problem. These tools offer high accuracy and save time. They also reduce costs significantly. This study uses specific machine learning algorithms for its goals. It follows a modern analytical path.

Many researchers study the unemployment rate in literature. Montgomery et al. (1998) compare linear and nonlinear models for the US. Their results show a clear improvement in estimation accuracy [1]. Chen (2008) investigates annual rates across ten countries with the NGBM model [2]. Dumičić et al. (2015) evaluate estimation methods for several European nations. Different methods work better for different countries [3]. Dritsakos and Klazoglou (2018) apply SARIMA and GARCH models to US data [4]. Claveria (2019) includes consumer expectation consensus to improve results [5]. Maas (2020) tests Google search data for US unemployment trends. This study finds high effectiveness for short-term

predictions [6]. Chakraborty et al. (2021) propose a hybrid approach using linear and nonlinear models. This method shows promising results against traditional tools [7]. Davidescu et al. (2021) conduct a comparative analysis of univariate time series methods [8]. Simionescu and Cifuentes-Faura (2022) analyze youth unemployment in Spain with Google Trends indices [9]. Jo et al. (2023) develop a stock-flow model using a system dynamics approach. Their work incorporates GDP growth and inflation rates [10]. Huruta (2024) estimates Indonesian unemployment with non-seasonal ARIMA models [11]. Gayaker and Türe (2025) use Google Trends data to enhance unemployment estimates across various disciplines [12].

Literature includes many studies combining unemployment rates and machine learning algorithms. Mulaudzi and Ajoodha (2020) apply different machine learning methods for South Africa. These algorithms outperform traditional statistical techniques in their tests [13]. Katris (2020) analyzes time series and machine learning models for unemployment across several countries [14]. Gogas et al. (2022) use decision trees, random forests, and support vector machines for the Eurozone. The random forest algorithm provides the best estimation results in this study [15]. Gupta et al. (2022) utilize random forests to study oil price uncertainty and UK unemployment. They examine a long dataset spanning from 1859 to 2020 [16]. Yurtsever (2023) presents a new model with LSTM and GRU layers. The hybrid model performs better for four specific countries [17]. Yamacli and Yamacli (2023) demonstrate the performance of ARIMA and ANN algorithms in their research [18]. Güler et al. (2024) estimate monthly unemployment rates in Turkey using machine learning. Their results show that these algorithms work effectively for macroeconomic studies [19]. Chen et al. (2025) develop a deep learning model for GDP per capita estimation. They incorporate the consumer price index and unemployment rates to increase accuracy. The study applies five different deep learning models to real and placebo datasets [20]. This study focuses on the official unemployment rate in Türkiye within the current literature. It uses seasonally adjusted labor force indicators and employment data by sector to estimate these rates. The main objective involves applying different machine learning algorithms to the Turkish dataset. The research determines which specific algorithm shows the most successful estimation performance. Additionally, the study identifies the most effective variables for unemployment through a feature selection algorithm. To estimate the unemployment rate, a critical macroeconomic indicator for the Turkish economy, this study combines machine learning algorithms and feature selection processes, moving beyond traditional methods. While existing literature often focuses on singular models, this research aims to fill the methodological gap by providing a comparative analysis of RBF, SVM, and Random Forest algorithms and identifying the most influential variables through the ReliefF algorithm. By doing so, this study contributes to the literature by determining which specific algorithm shows the most successful estimation performance for the Turkish dataset.

2. Materials and Methods

2.1. Data Set

This study focuses on predicting the unemployment rate in Türkiye based on its core objectives. It uses seasonally adjusted labor force indicators and employment data by sector to estimate future rates. The research obtains all necessary variables from the Turkish Statistical Institute website. The TurkStat data portal provides direct access to these figures. The dataset includes quarterly observations from 2005 to 2025. This period covers data up to the third quarter of 2025. The study selects the unemployment rate in Türkiye as the primary dependent variable. It defines several independent variables under the labor force indicators category. These include population aged 15 and over, those not in the labor force, the labor force participation rate, and the employment rate. The model also incorporates independent variables from the employment by sector category. These variables represent the agriculture, industry, construction, and services sectors. Table 1 presents the definitions of all variables used in this work. Table 2 provides the relevant descriptive statistics for the dataset. Figure 1 displays the general trends in the Turkish unemployment rate between 2005 and 2025.

Table 1. Variables used in the study and definitions

<i>Variables</i>	<i>Definition</i>	<i>Variable type</i>
Population 15 years and over (thousand person)		Independent variables

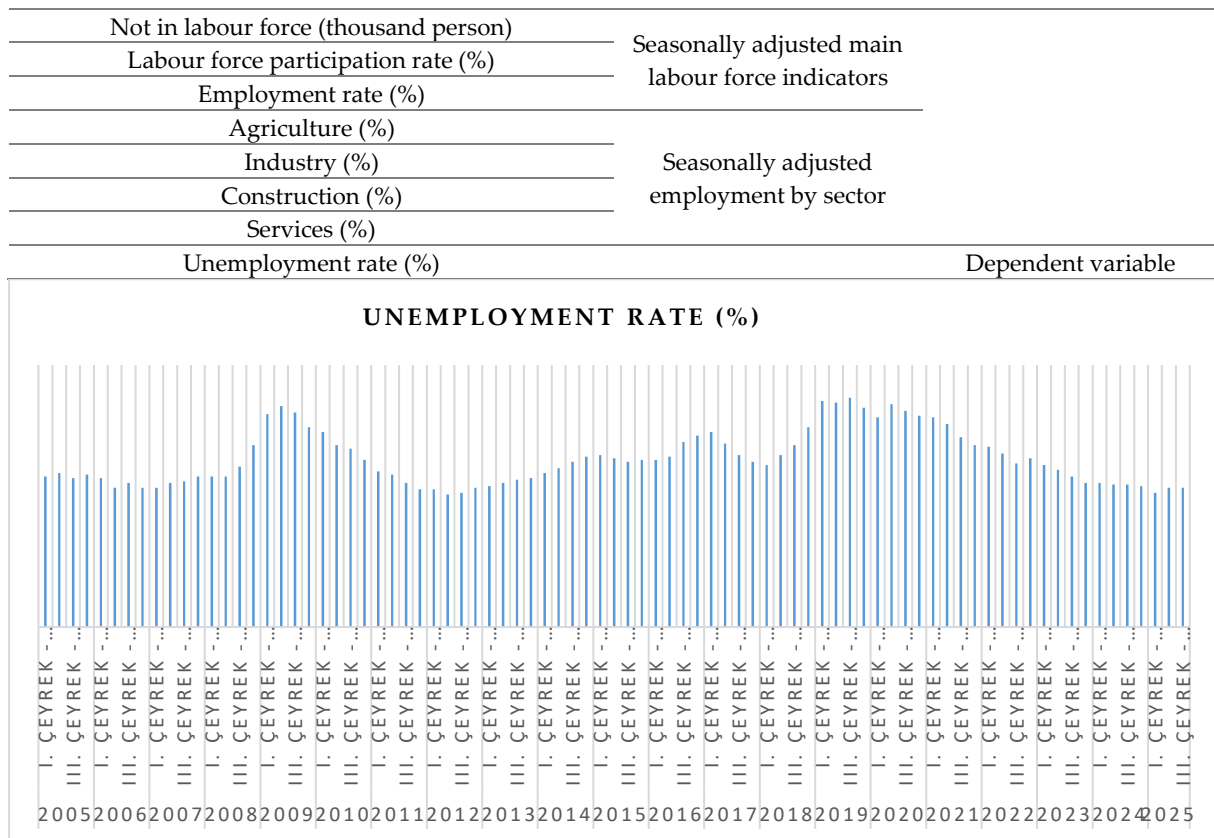


Figure 1. Unemployment rate display for 2005-2025 (including the 3rd quarter results, 4th quarter data are not yet available for 2025)

Table 2. Variables descriptive statistics values

<i>Variables</i>	<i>Maximum value</i>	<i>Minimum value</i>	<i>Average value</i>	<i>Standard deviation</i>
Population 15 years and over (thousand person)	66.458	48.013	57.644	5657.270
Not in labour force (thousand person)	32.685	26.831	29.033	1222.355
Labour force participation rate (%)	54.2	43.4	49.3	3.6
Employment rate (%)	49.5	39.0	44.2	3.1
Agriculture (%)	26.4	14.0	19.8	3.1
Industry (%)	22.6	19.1	20.7	0.8
Construction (%)	7.7	5.2	6.5	0.6
Services (%)	59.3	46.9	52.8	3.3
Unemployment rate (%)	14.0	8.1	10.2	1.6

2.2. Algorithms

This study focuses on estimating the unemployment rate in Türkiye. Seasonally adjusted main labor force indicators and seasonally adjusted employment data by sector variables will be used to estimate this variable. In line with the literature, various machine learning algorithms will be used to estimate the unemployment rate in Türkiye. In this context, the performance of Radial Basis Function (RBF) Regression Machine Learning Algorithm [22-24], Support Vector Machines (SVM), Regression Machine Learning Algorithm [14, 25-27], and Random Forest (RF) Decision Tree [15,28,29] algorithms for estimating the unemployment rate will be examined.

Additionally, in line with the literature, the ReliefF Feature Selection Algorithm [30-32] will be used to determine the effective variables the unemployment rate estimation in Türkiye. Furthermore, k-fold cross-validation will be utilized. In k-fold cross-validation, the k-value is generally set as 10. The literature suggests that the value of k=10 yields, more robust compared to other values. Under this

method, the data is divided into 10 equal parts, 9 parts are used as the training data set, and the remaining 1 part as the test data set. This process is repeated 10 times, and the result is obtained by averaging the 10 resulting values [33, 34]. In contrast to random partitioning, an approach was adopted, ensuring that the testing set always covers a period after the training set. This allowed for an objective evaluation of the models' real-time predictive capabilities. The analysis in this study will be conducted using the open-source Weka software. The parameters of the algorithms used in the study are shown in Table 3.

Table 3. Parameters of the algorithms used in the study

	Support Vector Machines	RBF Regression	Random Forest
Batch Size	100	100	100
Debug	False	False	False
Do Not Check Capabilities	False	False	False
Num Decimal Places	2	2	2
Num Functions	-	2	-
Num Threads	-	1	-
Pool Size	-	1	-
Ridge	-	0.01	-
Scale Optimization Option	-	Use scale per unit	-
Seed	-	1	1
Tolerance	-	1.0E-6	-
Use Attribute Weights	-	False	-
Use CGD	-	False	-
Use Normalized Basis Functions	-	False	-
c	1.0		-
Filter Type	Normalize Training Data	-	-
Kernel	Poly Kernel	-	-
Reg Optimizer	Reg Smo Improved	-	-
Bag Size Percent	-	-	100
Break Ties Randomly	-	-	False
Calc Out of Bag	-	-	False
Compute Attribute Importance	-	-	False
Max Depth	-	-	0
Num Execution Slots	-	-	1
Num Features	-	-	0
Num Iterations	-	-	100
Output Out of Bag	-	-	False
Complexity Statistics	-	-	False
Print Classifiers	-	-	False
Store Out of Bag Predictions	-	-	False

2.2.1. Radial Basis Function (RBF) Regression Machine Learning Algorithm

The study uses the Radial Basis Function (RBF) Regression algorithm to estimate the unemployment rate in Türkiye. This algorithm trains in a fully supervised manner by minimizing squared errors. It functions as a network of radial basis functions. The model produces accurate results for both estimation and classification tasks. Users find this algorithm under the 'RBFRegressor' heading in the Weka software. The model utilizes Gaussian radial basis functions for its calculations. It adjusts initial sigma values based on the maximum distance between centers and their nearest neighbors. The output layer uses an approximate logistic function as its activation function. This choice increases overall computational efficiency. The general structure of the model resembles an artificial neural network. It consists of an input layer, a hidden layer, and an output layer with one or more nodes [22, 35-37].

2.2.2. Support Vector Machines (SVM) Regression Machine Learning Algorithm

The Support Vector Machines (SVM) Regression algorithm estimates the unemployment rate in Türkiye for this study. This method works well for both prediction and classification tasks. It operates under the 'SMOreg' heading in the Weka software. The model learns parameters through various algorithms. It

relies only on a subset of the training data. The cost function ignores any data points close to the model prediction. The algorithm functions by setting a specific regression optimizer. SVM uses different kernel functions to process data effectively. These include the Polynomial kernel, the Pearson VII universal kernel, and the String kernel. The choice of kernel significantly affects the learning capacity of the model. Different kernels show varying results in the literature. This study uses the polynomial kernel function for analysis [14, 38, 39].

2.2.3. Random Forest (RF) Decision Tree Machine Learning Algorithm

The Random Forest (RF) Decision Tree Machine Learning Algorithm, which will be used to estimate the unemployment rate in Türkiye for the purposes of this study, is a decision tree algorithm used in estimation and classification problems, like the other machine learning algorithms used in this study. This decision tree algorithm generally considered to be more successful than other decision trees [40]. The algorithm, which uses variations of training data to develop multiple decision trees, randomly samples some parts of the original training data to obtain new versions of the training data. Each tree is grown as far as possible without pruning. Each tree is then used to form its own classification or estimation, and the final decision is determined through a majority vote or averaging [28, 41].

2.2.4. ReliefF Feature Selection Algorithm

This study uses machine learning algorithms to estimate the unemployment rate in Türkiye. The ReliefF Feature Selection Algorithm identifies the specific variables influencing these estimates. Feature selection serves as a standard practice in machine learning tasks. It determines which variables impact the dependent variable most. The process repeats using only these effective variables. Similar results are expected when using only the top variables compared to the full dataset. This approach increases overall efficiency. It achieves high performance with fewer data points. The ReliefF algorithm evaluates feature importance through repeated sampling. It compares feature values between the closest examples of the same and different classes. This method works successfully on both discrete and continuous datasets. Conceptually, the algorithm minimizes distances between instances of the same class. It maximizes distances between instances of different classes [31, 42, 43].

2.2.5. Machine Learning Algorithm Prediction Performance Measures

This study uses machine learning algorithms to estimate the unemployment rate in Türkiye. Specific measures evaluate the performance of these models. The research utilizes Correlation Coefficient (CC), Kendall's Tau, Mean Absolute Percentage Error (MAPE), Direction Accuracy (DAC), and Mean Absolute Error (MAE). The Correlation Coefficient serves as a critical measure for estimation performance. A CC value closer to 1 indicates a better model. Similarly, researchers expect Kendall's Tau value to be as high as possible. Higher values in this measure lead to more accurate results. DAC value acts as the primary performance measure in this study. Algorithms with high DAC produce the best results when other measures support them. The Directional Accuracy (DAC) metric employed in this study measures not only the model's success in predicting the numerical value of the target variable but also its ability to correctly forecast the period-to-period change in the unemployment rate. Conversely, MAPE and MAE indicate estimation errors. Smaller values for these two measures signify more successful models. The formulas for the Machine Learning Algorithm Prediction Performance Measures used in the study are given below:

$$CC = \frac{\sum_{t=1}^n (y_t - \bar{y})(\hat{y}_t - \bar{\hat{y}})}{\sqrt{\sum_{t=1}^n (y_t - \bar{y})^2 \sum_{t=1}^n (\hat{y}_t - \bar{\hat{y}})^2}} \quad (1)$$

$$Kendall's\ Tau = \frac{C - D}{\frac{1}{2}n(n - 1)} \quad (2)$$

$$MAPE = \frac{100\%}{n} \sum_{t=1}^n \left| \frac{y_t - \hat{y}_t}{y_t} \right| \quad (3)$$

$$DAC = \frac{1}{n-1} \sum_{t=2}^n D_t * 100 \quad (4)$$

$$MAE = \frac{1}{n} \sum_{t=1}^n |y_t - \hat{y}_t| \quad (5)$$

3. Application

This study uses machine learning algorithms to estimate the unemployment rate in Türkiye. The research examines the estimation performance of each model. A feature selection algorithm identifies the specific variables affecting these estimates. The application section consists of four distinct phases. Phase 1 determines the performance of different machine learning algorithms using all available variables. Phase 2 identifies the most important variables and their levels of influence through a feature selection algorithm. Phase 3 re-evaluates the performance of the machine learning algorithms using only these effective variables. Finally, Phase 4 compares the results of the algorithms based on both the full dataset and the selected variables.

The application scheme of the study is shown in Figure 2.

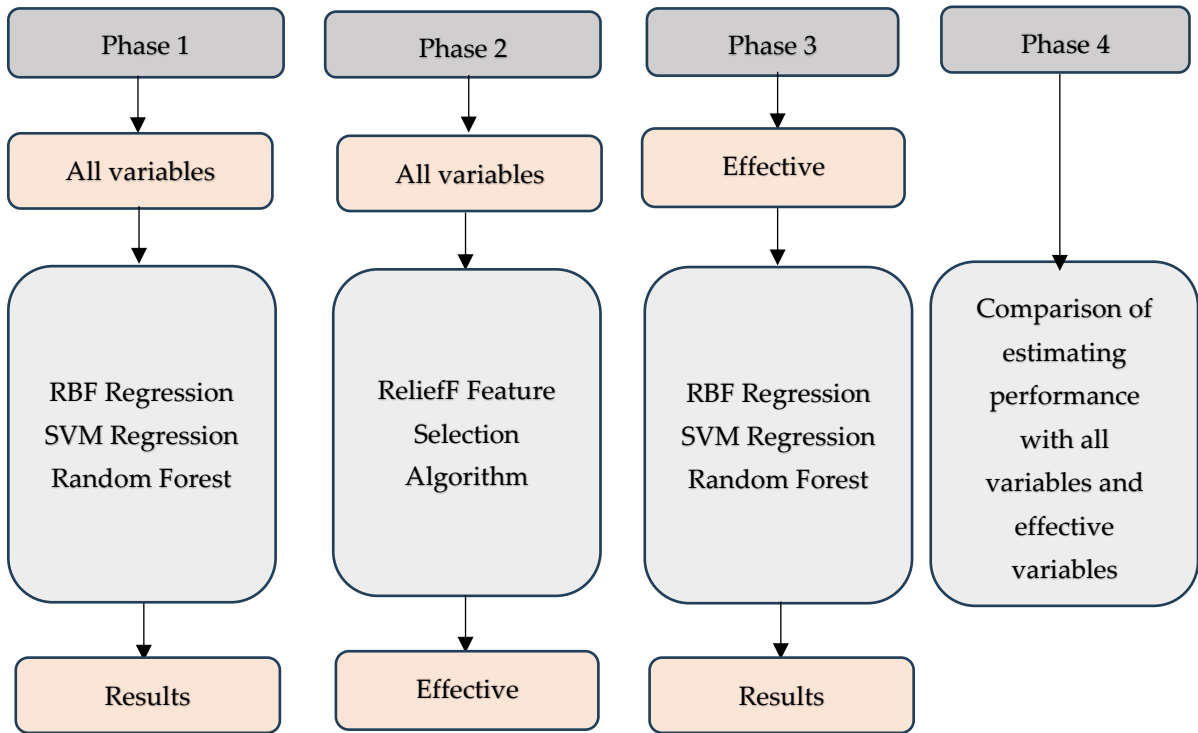


Figure 2. The application scheme of the study.

In addition to the phases mentioned, the primary aim of this study is not to recalculate the known mathematical identity between the unemployment rate and its components, but to test the extent to which machine learning algorithms can model the complex and nonlinear interactions between these variables. Unlike traditional models, methods such as RBF, SVM, and Random Forest learn structural dependencies through a data-driven approach. This process validates the algorithms' capacity to capture hidden patterns within economic indicators and demonstrates the flexibility of machine learning in macroeconomic analysis.

4. Results

In line with the research goal, machine learning algorithms estimate the unemployment rate in Türkiye. The study examines the estimation performance of each model. Additionally, the ReliefF Feature Selection Algorithm determines the most effective variables for these predictions.

Following Phase 1, the research evaluates different machine learning algorithms using the full set of variables. Table 4 presents the detailed results of these estimations.

Table 4. Estimation performance of machine learning algorithms for the unemployment rate using all variables

	RBF Regression	SVM Regression	Random Forest
CC	0.8842	0.9815	0.9483
Kendall's Tau	0.6648	0.8780	0.7996
MAPE	0.0557	0.0211	0.0453
DAC	78.57%	91.43%	88.57%
MAE	0.2634	0.0065	0.1777

According to Table 4, the study examines the performance of different machine learning algorithms using all variables. The SVM Regression algorithm shows the most successful estimation performance. It achieves the highest DAC value of 91.43%. Other measures support this result with a CC value of 0.9815 and a Kendall's Tau of 0.8780. The algorithm also shows low error rates with a MAPE of 0.0211 and an MAE of 0.0065. The Random Forest algorithm follows closely with a DAC value of 88.57%. Conversely, the RBF Regression algorithm displays the lowest performance with a DAC value of 78.57%. The MAE (0.0065) and other error metrics reported in Table 4 were calculated based on the normalized dataset within the (0, 1) range. This normalization was performed to standardize variables with different scales and ensure the consistency of the estimation performance. Consequently, the error metrics reflect this normalized scale. Even when back transformed to the original data scale, the models demonstrate high precision within acceptable academic limits.

Following Phase 2, the ReliefF Feature Selection Algorithm identifies the effective variables for the unemployment rate. It also determines their respective importance levels. Table 5 presents these specific results.

Table 5. Variables and their importance levels affecting unemployment rate prediction using the ReliefF attribute selection algorithm

Effective variables	Importance levels
Industry	0.0449
Construction	0.0338
Employment rate	0.0298
Labour force participation rate	0.0164

According to Table 5, the primary variables influencing the unemployment rate estimation in Türkiye are identified. These variables include 'Industry' (0.0449), 'Construction' (0.0338), 'Employment rate' (0.0298), and 'Labor force participation rate' (0.0164).

Following Phase 3, the study determines the performance of different machine learning algorithms using only these effective variables. Table 6 presents the detailed results of these estimations.

Table 6. Estimation performance of machine learning algorithms for the unemployment rate using effective variables

	RBF Regression	SVM Regression	Random Forest
CC	0.8936	0.9688	0.9171
Kendall's Tau	0.7111	0.8359	0.7052
MAPE	0.0536	0.0263	0.0512
DAC	%72.86	%91.42	%88.57
MAE	0.2829	0.0065	0.2796

According to Table 6, the study examines the performance of various machine learning algorithms using only the effective variables. The SVM Regression algorithm demonstrates the most successful estimation performance, achieving a high DAC value of 91.42%. Other metrics reinforce this result, including a CC value of 0.9688, a Kendall's Tau of 0.8359, a MAPE of 0.0263, and an MAE of 0.0065. The Random Forest

algorithm performs similarly, yielding a DAC value of 91.71%. In contrast, the RBF Regression algorithm shows the lowest performance, with its DAC value falling to 72.86%.

Following Phase 4, the research compares the performance of these algorithms across both the full set of variables and the selected effective variables. Figures 3 and 4 illustrate these comparisons.

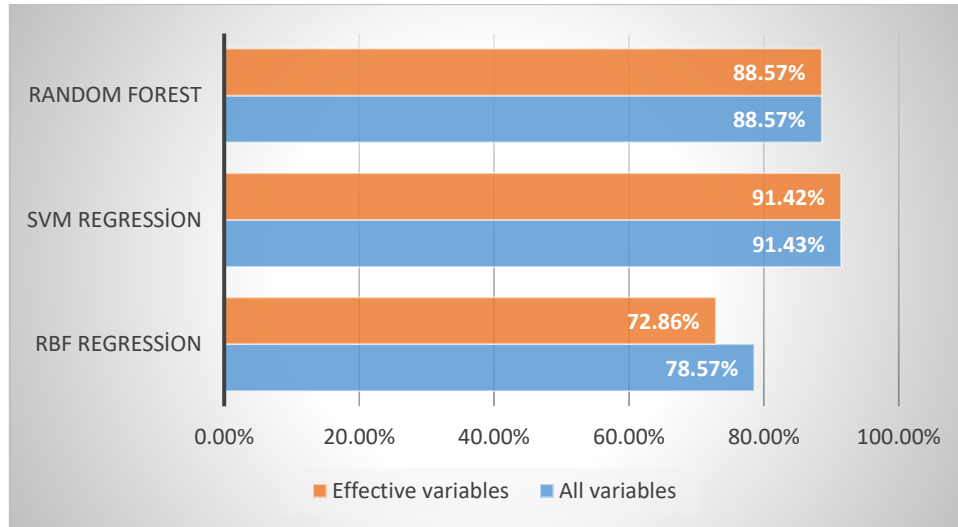


Figure 3. Comparison of DAC values for unemployment estimation performance using all variables and effective variables

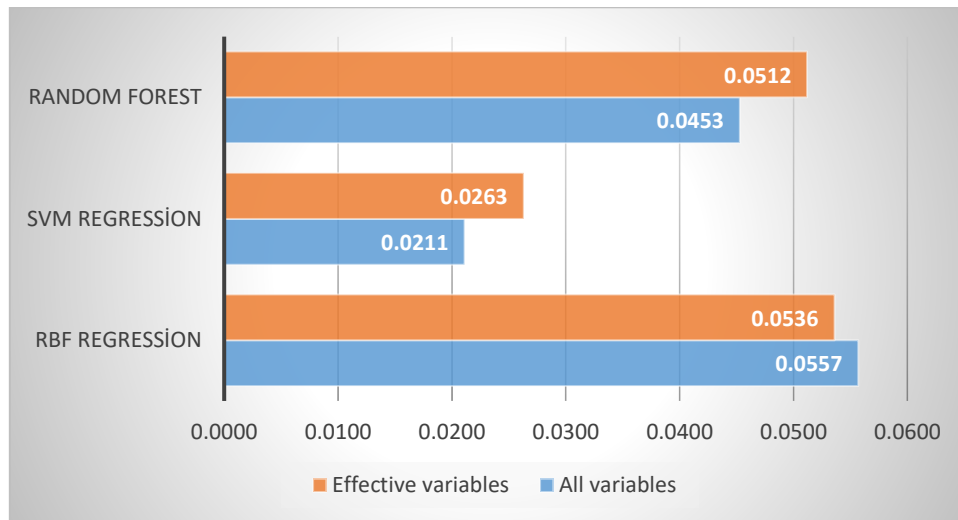


Figure 4. Comparison of MAPE values for unemployment estimation performance using all variables and effective variables

Figure 3 compares the DAC values for unemployment estimation performance using both the full set of variables and the selected effective variables. Overall, the Random Forest and SVM Regression methods maintain consistent estimation performance across both variable sets. However, the RBF Regression model shows a decrease in success when using only effective variables compared to the full dataset. Figure 4 illustrates the comparison of MAPE values for the same models. In this case, the Random Forest and SVM Regression methods show an increase in error measures when moving from all variables to effective variables. Conversely, for the RBF Regression algorithm, the error measure decreases when using the effective variables compared to the original set.

4. Discussion

The findings of this study demonstrate that machine learning algorithms are highly effective in estimating the unemployment rate in Türkiye. Success rates for these models range between 79% and 91%. In the first phase of the analysis, SVM Regression emerges as the most successful algorithm when

using all variables. This result aligns with the existing literature. It corroborates the effectiveness of SVM Regression reported by Sermpinis et al. (2014), Ülker and Ülker (2019), and Ahmad et al. (2023). [26, 44, 45].

According to Phase 2, the primary variables influencing the unemployment rate estimation in Türkiye are 'Industry', 'Construction', 'Employment rate', and 'Labor force participation rate'. Among these, the 'Industry' variable is identified as a particularly critical factor. This finding aligns with several studies in the literature that highlight the industrial sector as a major driver of national employment trends. The significance of this variable confirms that fluctuations in industrial production and capacity directly impact the broader labor market. [46-49]. Similarly, the 'Construction' variable has been identified as a key determinant of the unemployment rate in the literature [48-52]. Similarly, the influence of labor market indicators like the employment rate and participation rate supports the findings of Ozerkek (2013), Yildirim (2014), Kanlıoğlu and Dumludağ (2022), Burger and Šlampaiková (2025), and Zaheer Khan et al. (2024) [53-57]. These alignments reinforce the validity of the variables chosen for the Turkish macroeconomic context.

Phase 3 provides critical observation. Estimation accuracy does not decrease significantly. The ReliefF algorithm identifies effective variables. Only these variables are used. Some performance measures show improvement. Feature selection simplifies the model. It removes noise. This process increases predictive power.

The findings reveal that employment in the industrial and construction sectors is the most critical leading indicator in determining the unemployment rate in Türkiye. From an economic perspective, this suggests that combating unemployment can be managed more effectively through sectoral incentives targeting these two engine sectors, rather than solely through general macroeconomic policies. The high directional accuracy (91% DAC) of the SVM model enables policymakers to anticipate unemployment trends and develop proactive employment strategies. These results prove that the unemployment rate in the Turkish economy is structurally and directly linked to industrial production capacity and construction investments.

5. Conclusions

This study applies machine learning techniques to estimate the unemployment rate in Türkiye. The analysis uses seasonally adjusted labor force and sector-based employment data. The study compares RBF Regression, Random Forest, and SVM Regression. SVM Regression consistently provides the most accurate results for this macroeconomic dataset. The research identifies the most influential variables through the ReliefF algorithm. These sectors and indicators provide a scientific basis for policymakers. Machine learning models yield reliable results with fewer variables. This approach offers a more efficient way to forecast economic trends.

The study has certain limitations. The analysis uses the Turkish Statistical Institute dataset from 2005 to late 2025. Data for the final quarter of 2025 is not included. Future research can incorporate more recent data. New studies may explore hybrid deep learning architectures to improve accuracy.

Author Contributions: All stages of the study were developed by the author.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

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