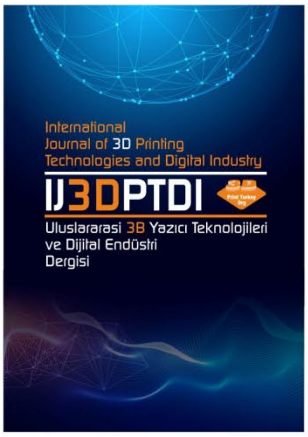

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PREDICTION OF HARDNESS VALUES OF AGED SELECTIVE LASER MELTED AlSi10Mg ALLOY DATA WITH MACHINE LEARNING METHODS

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ABSTRACT

Aluminum manufactured with the Selective Laser Melting (SLM) method has been the subject of many research due to the benefits it provides, especially when used in the automotive and aviation industries. Therefore, it is important to examine and improve the mechanical properties of Al parts produced by the SLM method. Many experiments are needed to examine and improve the mechanical properties of SLM Al materials. This situation causes losses in terms of both time and cost. In this study, aims to estimate the hardness values of SLM AlSi10Mg materials that have been aged. For this purpose, aging processes were applied to SLM AlSi10Mg materials at different times and temperatures, and different machine learning methods were used to predict the hardness values using the hardness values obtained because of the process. Random Forest Regression (RFR) algorithm and Artificial Neural Network (ANN) were used in the study. As a result of the study, it was determined that the hardness values estimated by the ANN (R^2 0.9276) method were close to the real hardness values. This is proof that it is possible to predict hardness values using the machine learning method.

Keywords: SLM, AlSi10Mg, Aging, Artificial Neural Networks, Machine Learning, Regression

1. INTRODUCTION

Additive Manufacturing (AM), unlike other manufacturing methods, is used to create machine parts by adding materials step by step and covers all 3D manufacturing methods [1]. 3D manufacturing technology has developed considerably in recent years due to the increased need for personalized production, lightweight structure design and smart production [2-5]. In addition, the 3D manufacturing method offers design freedom and low-cost opportunities due to low material loss [6]. Selective Laser Melting (SLM) method, one of the 3D manufacturing methods, attracts attention due to its production accuracy and high designability [7-9]. Due to these features, the SLM method is used in industrial applications that require advanced technology such as automotive, aviation and shipbuilding [10-12]. Steel, nickel, titanium and aluminum alloys are preferred as materials in the SLM method. AlSi10Mg materials have many outstanding properties such as excellent corrosion resistance, thermal conductivity, impressive strength-to-weight ratio..Having these properties, this alloy is preferred in areas where high performance and lightness are important. In addition, AlSi10Mg alloys are preferred in complex designs due to their surface quality and superior stability properties. In addition to all these features, it is compatible with metal 3D printing methods and selective laser melting (SLM) method. For this reason, it has become the preferred material in 3D manufacturing [13,14]. The mechanical properties of AlSi10Mg parts produced by the SLM method are significantly improved compared to the parts produced by the high-pressure casting and die casting methods [15-17]. The mechanical properties of SLM parts were improved by heat treatment [18-21]. Li and his colleagues determined that elongation and the tensile strength can be improved by controlling the morphology of Si by applying a special heat treatment to the parts manufactured by the AM method [22]. Thermal processes applied to Al-Si-Mg alloys are solution, quenching, natural or artificial aging. operations [23]. If the solution process is applied to these alloys, spheroidization and structure become homogeneous in the Si phase [24]. In their study, Zhuo et al. determined that there was an increase in the elongation and a decrease in the strength of SLM samples subjected to stress relief annealing at 300 °C [8]. In their study, Maamoun et al. concluded that high temperature solid solution heat-treatment worsened the hardness values of the samples applied [25]. When literature is examined, it is seen that controlling the process temperature and waiting time is important during heat treatment of the samples manufactured by the SLM method. Considering this situation, the importance of optimizing the aging process temperature, time and cooling environment to improve the mechanical properties of AlSi10Mg parts manufactured by the SLM method emerges. Many experiments are needed for optimization. For this reason, many researchers have used various machine learning techniques in their studies to better understand input relationships and identify factors in obtaining an optimized prediction model [26]. Many researchers have successfully employed ANN, a machine learning technique noted for its excellent reliability and prediction capability [17-29]. For this purpose in this study, aging processes were applied to SLM AlSi10Mg materials at different times and temperatures, and different machine learning methods were used to predict the hardness values using the hardness values obtained because of the process.

The rest of the paper is organized as follows; the materials and methods utilized in the study are described in Section 2. The application and assessment of machine learning techniques on the experimental study data are described in Section 3. The last part concludes the study.

2. MATERIAL AND METHOD

2.1. Experimental Procedure

In this study, 20-70mm spherical AlSi10Mg powder was used. The chemical properties of the powder used in the study are given in Table 1.

Table 1. Chemical Composition of AlSi10Mg

Element(%w)	Al	Si	Fe	Cu	Mn	Mg	Zn	Ti	Ni	Sn
	The rest	9-11	≤0.55	≤0.05	≤0.45	0,2-0.45	≤0.1	≤0..5	≤0.05	≤0.05

In this study, samples of AlSi10Mg material were manufactured by the SLM method. SLM samples were produced in a 250mmx250mmx325mm production room using Yb-fiber laser on the EOS M 290 system.400W laser power, 7m/s scan speed, 100µm focus diameter and 100psi compressed air application were selected as process parameters in sample production. A prismatic sample with dimensions of 10*10*5 mm was used in the study.

In this study, it was aimed to determine the effect of the aging process on the hardness of samples produced by the SLM method. For this purpose, the aging processes applied to the samples are given in Table 2.

Table 2. Heat treatment parameters applied to the samples

Process	Parameter
Solution Heat Treatment	415°C 2 h solution HT + that water-cooled 415°C 2 h solution HT + air cooling 515°C 1.5 solution HT after that water cooling 540°C 1 h solution HT after that water cooling
Solution Heat Treatment + aging treatment	515°C 1 h water cooling + 160°C 10h air cooling 515°C 1 h water cooling + 160°C 14h air cooling 515°C 1 h water cooling + 160°C 18h air cooling 515°C 1 h water cooling + 160°C 10h indoor cooling 515°C 1 h water cooling + 160°C 14h indoor cooling 515°C 1 h water cooling + 160°C 18h indoor cooling 540°C 1 h water cooling + 180°C 8h air cooling 540°C 1 h water cooling + 180°C 12h air cooling 540°C 1 h water cooling + 180°C 16h air cooling 540°C 1 h water cooling + 180°C 8h indoor cooling 540°C 1 h water cooling + 180°C 12h indoor cooling 540°C 1 h water cooling + 180°C 16h indoor cooling

The workflow of the study and aging process applied for the study is given in Figure 1.

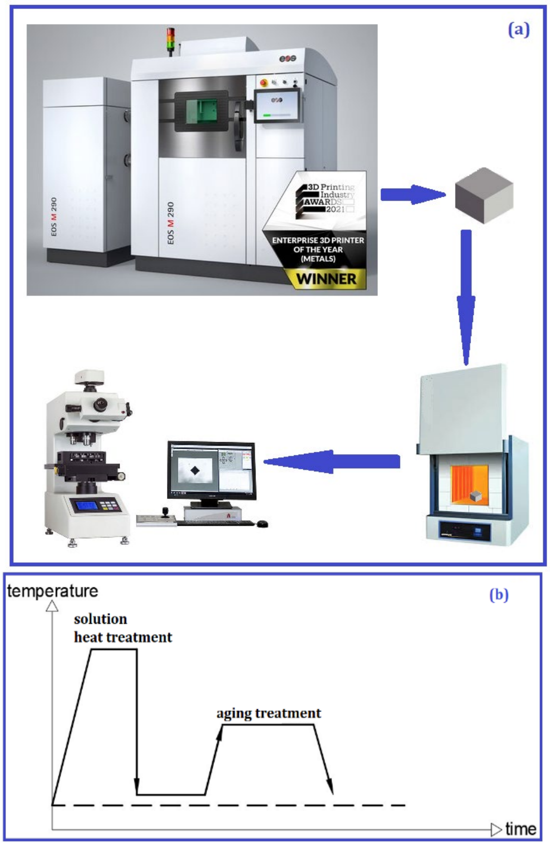

Figure 1. (a) Workflow of the study (b) Heat treatment procedure applied to AlSi10Mg samples

In the experimental work, Protherm HLF100 type heat treatment furnace was used for the aging process. In order to determine the change in the hardness of the samples after the aging process, the hardness values of the samples were measured using the TTS Matsuzawa HWMMT-X3 micro hardness device with an applied load of 10 g for 10 s.5 measurements were made on each sample and the arithmetic average was taken. Microstructural examinations were carried out on samples with and without the aging process. Before microstructural examinations, the samples were polished and then etched using Keller reagent [30]. FEI QUANTA FEG 250 Scanning electron Microscope (SEM) was used for surface investigations.

2.2. Machine Learning Methods

In this study, aging processes were applied to SLM AlSi10Mg materials at different times and temperatures were used to predict the hardness values. For this purpose, Artificial Neural Network (ANN) and Random Forest Regressor (RFR) methods, popular machine learning methods, were used. Inspired by the human brain, artificial neural networks (ANNs) are computer models that can identify patterns and make decisions in a manner akin to that of biological neurons [31]. They can learn from data and generalize effectively to new cases, which makes them useful in domains like multivariable regression analyzes [32] and image recognition [33]. The input layer, hidden layers, and output layer are the three types of ANNs (Figure 2). First, data is received at the input layer and is processed using activation functions through hidden layers. The outcome of the classification or prediction is generated by the output layer. Complex computations are carried out via input layers, where each neuron applies a non-linear activation function after a linear translation. The model's prediction is produced by the final output layer, which is typically a single neuron with linear activation for regression tasks [34] or a softmax layer for classification tasks [35]. Another popular algorithm for regression problems is an ensemble learning technique called the Random Forest Regressor (RFR)(Figure 3). During training, RFR entails creating many decision trees and combining their predictions to increase the robustness and performance of the model [36]. This method improves the model's capacity for generalization while lowering overfitting. Bootstrap sampling, random feature selection, and aggregate prediction are the main elements of a random forest. A random portion of the training data is used to train each tree, and the total of all the trees' predictions is the final forecast [35]. The performance of the model is affected by the number of trees, the maximum depth of the trees, and the minimum number of samples required to split a node.

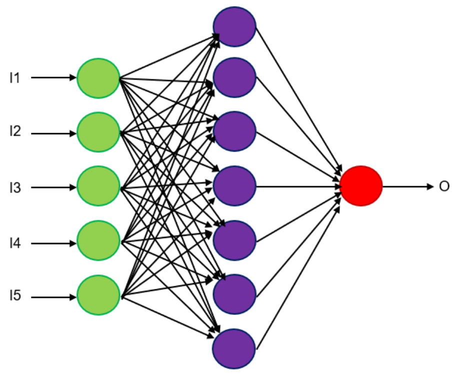

Figure 2. ANN structure of the study

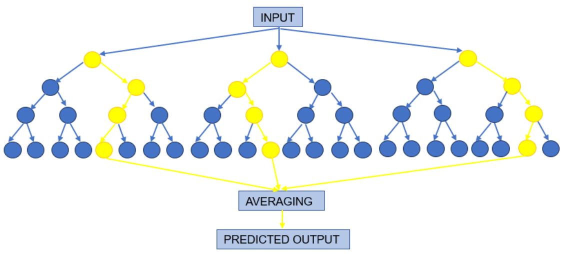

Figure 3. RFR structure of the study

ANNs are efficient in learning detailed patterns and interactions between features, making them useful in complex, non-linear data contexts like speech and image recognition [37]. On the other hand, RFRs work better with structured data that has distinct feature importance and relationships, and they are more efficient with simpler, piecewise linear data [38]. Additionally, they can manage missing values without requiring a lot of preprocessing and are resistant to overfitting. ANNs, however, are computationally demanding and need a large amount of memory and processing power with numerous layers and parameters [39]. (Distributed computers and GPUs can speed up ANN training, however RFRs are easier to train and can be parallelized effectively [40]. ANNs or RFRs are chosen based on the particular task requirements, data type, and resource availability.

2.3. Evaluation Metrics

Regression model performance in machine learning is assessed using a number of metrics, such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2). These measures shed light on the accuracy and error distribution of the model. The percentage of the dependent variable's variation that can be predicted from the independent variables is shown by R^2, sometimes referred to as the coefficient of determination [41]. Higher values of the ratio, which goes from 0 to 1, denote greater match. The average size of errors in a set of predictions, without considering their direction, is measured by the MAE. It offers an intuitive sense of the model's prediction accuracy in the same units as the target variable, making it simple to comprehend and apply [42]. The magnitude of the data, however, can have an impact on MAE, which does not penalize greater errors more than smaller ones. The average magnitude of the error is measured by the quadratic scoring procedure known as RMSE. The square root of the average of the squared discrepancies between the actual observation and the prediction is what it is. Because each term is squared before being averaged and the square root is taken, RMSE emphasizes greater errors more than smaller ones [43]. Because it is sensitive to outliers and penalizes greater errors more severely, it is often utilized in situations where large errors are especially undesirable.

When selecting amongst R-squared, MAE, and RMSE to assess the effectiveness of a regression model, it is crucial to take the particular context and data type into account. R^2 is helpful in determining the percentage of variance that the model explains, but as it doesn't take into consideration the size of the mistakes, it should be used in conjunction with other metrics [44]. In actual use, reporting a variety of metrics is frequently advantageous in order to have a thorough grasp of the model's performance. One can determine whether the model's mistakes are consistently minimal or if there are major outliers by combining the analysis of MAE and RMSE. To sum up, R^2, MAE, and RMSE are useful metrics for assessing regression model performance in machine learning.

3. RESULTS AND EVALUATION

3.1. Experimental Results

The aim of this study was to estimate the change in hardness during the aging process at different temperatures, durations and cooling environments. In addition, different solution temperatures were selected. For this purpose, AlSi10Mg samples manufactured by the SLM method were subjected to the aging process. While determining the solution temperatures for the study, the Al-Si binary phase diagram in the work of Silvia et al. was used and the binary phase diagram is given in Figure 4. [45]. These temperatures were chosen as 415, 515 and 540 °C below the eutectic point and agree with the literature [46].

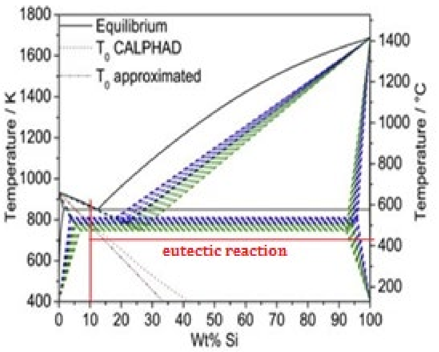

Figure 4. Phase diagram for Al-Si alloys [45]

The hardness values of the samples without aging were determined as 65HV. The solution temperature was 415°C, and the hardness values for the samples selected for both air cooling and water cooling were determined as 52 HRB (95HV). 53HV was obtained for the samples whose solution temperature was 540°C and the cooling environment in water was selected. The highest hardness value was measured as 57 HRB (102 HV) in the samples where the solution temperature was 515°C and the cooling medium was selected in water. After the solution process, Si particles and coarsening of the grain structure occurred. Additionally, during the solution process, the amount of dissolved Si in Al decreased, which agrees with the literature [47-48]. The coarsening in the microstructure and the decrease in the amount of Si caused a decrease in the hardness of the AlSi10Mg alloy manufactured by the SLM method after the solution process. The decrease in Si content in Al and the coarsened microstructure will lead to a decrease in the hardness of the SLM AlSi10Mg alloy after solution processing. In addition, the samples were taken into solution for 1 hour at 515 °C and 540 °C, and then aged at 160 °C for 10h, 14h and 18h. After the aging process, air and indoor were chosen as the cooling medium. When the samples in which water was used as the cooling medium were examined, it was determined that the highest hardness value was 86 HV in the samples with 14h aging process. These samples were followed by samples aged 18 h with a hardness value of 78 HRB (150 HV) and 10 h with a hardness value of 74 HRB (139 HV). When the hardness values were examined, the decrease in the hardness value with increasing processing time was determined to be a result of excessive aging. Additionally, with the quenching process, Si particles become spherical [49]. The quenching process causes rapid cooling and precipitation is stopped. The precipitates resulting from the solution process are thus stopped. During the aging process, these precipitates grow in the Al matrix and are evenly distributed in the matrix [14]. This allows us to adjust the mechanical properties of the AlSi10Mg alloy produced by SLM [50,51]. When the samples in which the cooling medium was selected as a indoor were examined, it was determined that the highest hardness value was 73 HRB (137 HV) in the samples with 10h aging process. These samples were followed by samples that were aged for 18h with a hardness value of 68 HRB (122 HV) and 14h with a hardness value of 64 HRB (112 HV). If the cooling medium was selected as a indoor, the hardness values obtained were lower than when cooled in air. Uncontrolled cooling process causes the formation of undesirable precipitate phases. These precipitations will cause a decrease in hardness. Additionally, this can be explained because of over aging. A correct cooling process should be as slow as possible and as fast as necessary [50]. When the hardness values of the samples, where the solution temperature was selected as 540°C and air cooling was applied after aging at 160°C for 8h, 12h and 16h, were examined, the hardness values were obtained as 67 HRB (120 HV), 62 HRB (110 HV) and 57 HRB (100 HV) at 12h, 16h and 8h processing times, respectively. has been made. This situation is similar to the samples that were subjected to solution at 515 °C. When the hardness values of the samples whose solution temperature was selected as 540°C and which were cooled in the indoor after aging at 160°C for 8h, 12h and 16h were

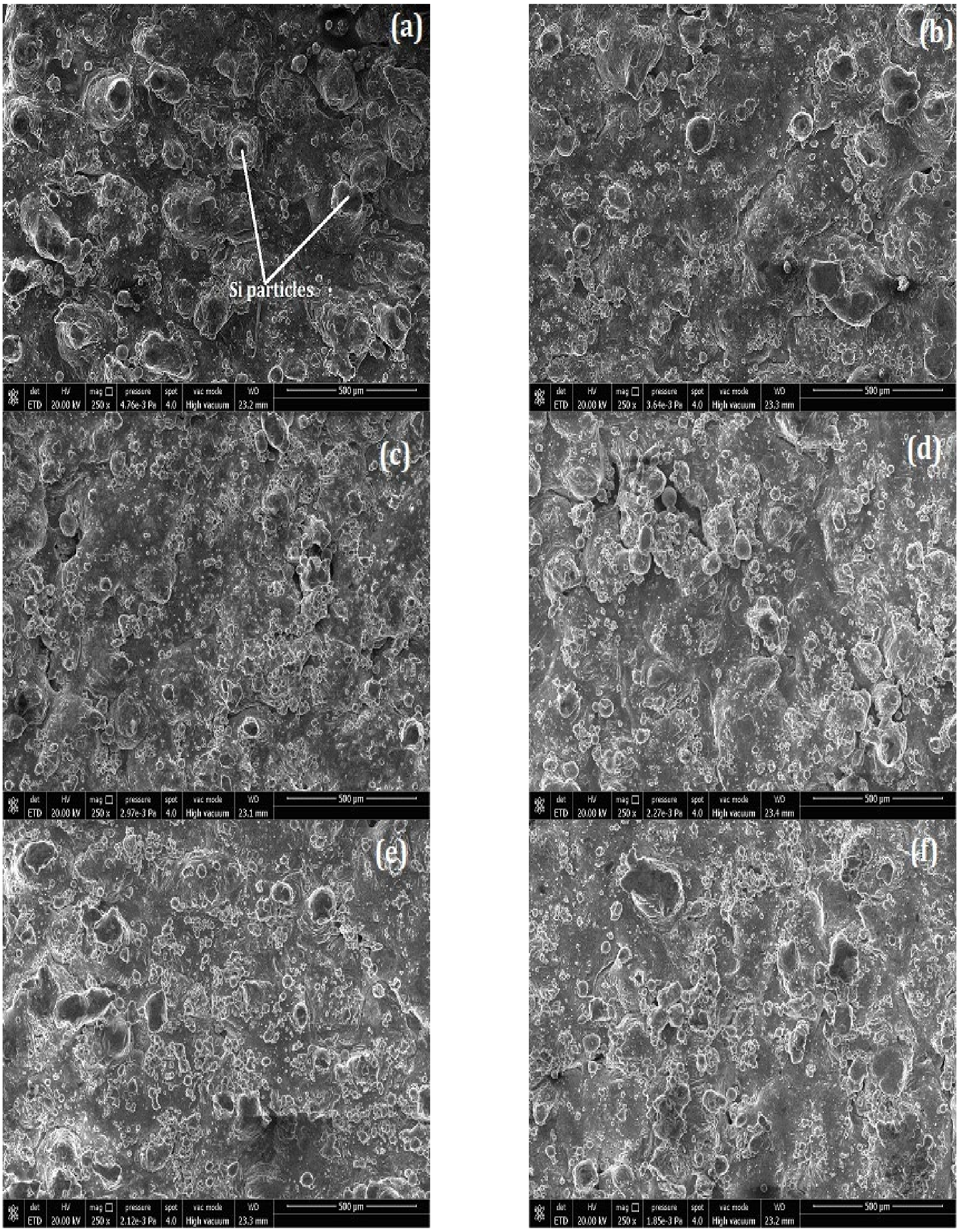

Figure 5. SEM images of the samples subjected to at different solution treatment, aging temperature and time (a) 515°C 1 h water cooling + 160°C 18h indoor cooling (b) 515°C 1 h water cooling + 160°C 14h indoor cooling (c) 540°C 1 h water cooling + 180°C 16h air cooling (d) 415°C 2 h water cooling (e) 515°C 1 h water cooling + 160°C 14h air cooling (f) 540°C 1 h water cooling + 180°C 12h air cooling

examined, it was determined that the highest hardness value was obtained in the samples with 16h aging (59 HRB (105 HV)).The slow cooling rate in the indoor cooling process increased precipitation formation and caused a decrease in hardness. Microstructure examinations of AlSi10Mg samples, which were manufactured by the SLM method and then aged by solution at different temperatures and times, were examined. SEM images of the samples subjected to at different solution treatment, aging temperature and time are shown in Figure 5 is given. With the solution taking process, coarsening occurred in the Si grain structure. Si particles have a fish-scale and column-shaped structure. However, it was determined that this Si structure was disrupted after the solution process. Additionally, as the processing time increased, the hardness increased. However, as the processing time increased further, the grains became coarser and the equilibrium solubility decreased, resulting in a decrease in hardness.

3.2. Dataset

In this paper, it is aimed to estimate the hardness values of SLM AlSi10Mg materials that have aged with different temperatures and time. The experimental measurement data consists of solution heat treatment temperature (I1), solutution treatment process time (I2), aging treatment temperature (I3), aging process time (I4) and environment (I5) are used as inputs, while hardness value (O) is used as an output. For SLM AlSi10Mg examples, 12 distinct measurement data are available. Different training-test percentages was analyzed and then best results was founded as 80% of this data for training and the rest of the data for test.

3.3. Implementation Details

The suggested machine learning techniques in the study's application section were implemented using Python. GridSearchCV [63] was used to run algorithms and tune parameters on a computer system equipped with an Intel Core i7 13650HX Turbo Boost 4.9 GHz CPU and 16 GB RAM. The hidden layer of the ANN algorithm contains 1024 units. Batch size is 50, learning rate is 0.01, epoch is 100, and activation function is linear. The settings of the RFR method are as follows: random_state = 20, max_depth = 5, squared_error = criteria, and n_estimators = 100.

3.4. Testing and Evaluation

To use machine learning techniques, it is essential to correctly identify the features in the dataset. Consequently, the developed model can predict the properties of various combinations of aluminum materials that have not yet been developed, speeding up the search for workable materials with hardness values. Given this, the study proposed that machine learning models can be used to generate high-performing materials. Furthermore, ML techniques' ability to estimate data is significantly influenced by the quantity and caliber of the input dataset. Furthermore, the variety and breadth of input features can fully describe the underlying mechanisms. Using ML models to determine the hardness value, the algorithms' performance was evaluated in terms of R^2, RMSE, and MAE values (Table 3). R^2 0.9276, RMSE 0.0804, and MAE 0.0626 were the best outcomes for the ANN algorithm (Figure 6).

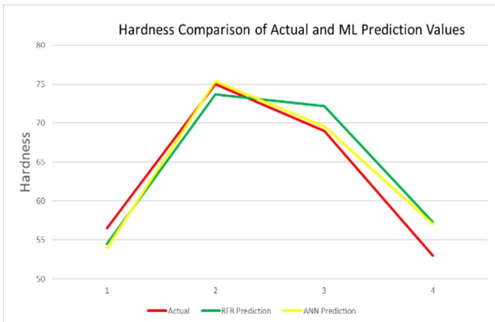

Figure 6. Comparison of actual and predicted values

Table 3. Estimation performances ML algorithms for hardness value estimation of different aluminum materials

Evaluation Metrics	ANN	RFR
R^2	0.9276	0.8930
RMSE	0.0804	0.0978
MAE	0.0626	0.090

The results show that in order to obtain the aluminum material with the highest hardness value, the ML algorithms produce results that significantly not different from the actual test data. The potential costs and waste of experiment time are decreased when machine learning algorithms are used for prediction tasks.

4. RESULTS

Aluminum metals are frequently used in many areas. Experiments are being carried out to obtain a durable and hard aluminum, and conducting many experiments creates a burden in terms of time and cost. For this reason, trying to obtain experimental results using machine learning methods from a certain number of experimental data without further experiments is a frequently used method. In this paper, the hardness values of aluminum materials that were aged for different periods of time in different environments were tried to be estimated by using ANN and RFR methods, which are well-known machine learning methods. When the experimental results were examined, a 26% increase in hardness was obtained in the samples subjected to 515 solution soaking and 160 14-hour aging processes. The results obtained were evaluated with performance measurement metrics such as R^2, RMSE and MAE, and it was shown that the ANN algorithm gave the best results and machine learning methods can be used successfully in satisfying the hardness values of aluminum materials. Therefore, it has been determined that being able to estimate aluminum materials without trying each time is advantageous in terms of time and cost.

ACKNOWLEDGES
The authors report no conflict of interest.

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