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# ARTIFICIAL INTELLIGENCE MODELS FOR PREDICTING ROOT TRAITS OF CHOKEBERRY UNDER SALT STRESS

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**Abstract:** Chokeberry (*Aronia melanocarpa*) is a recently introduced functional berry in Türkiye. It has a high health-promoting potential and growing commercial value. However, limited information is available regarding its physiological responses to abiotic stresses such as salinity. This study aimed to investigate the effects of salt stress on the root architecture of chokeberry plants grown in different growing media (soil and peat) and irrigated with five different salinity levels (0.65-10 dS $m^{-1}$). Root traits including fresh and dry weight, total root length, surface area, volume, average diameter, number of tips, forks, and crossings were measured using WinRhizo software. Additionally, the study employed machine learning algorithms XGBoost, Multilayer Perceptron (MLP), and Gaussian Process Regression (GPR) to predict root traits based on salinity levels and identify the most accurate predictive model. The results showed that increasing salinity significantly reduced all root growth parameters. Among the tested models, XGBoost achieved the highest predictive performance ($R^2 > 0.9$), followed by MLP and GPR. Fresh and dry root weights were predicted with 98% and 97-98% accuracy, respectively, while MLP was most effective in estimating surface area and root tips. However, predictions for average diameter, root volume, and root crossings showed lower accuracy (MAPE > 10%). The findings indicate that artificial intelligence-based models can successfully estimate chokeberry root responses to salt stress and offer a powerful tool for sustainable cultivation.

**Keywords:** Root architecture, Machine learning, XGBoost, Multilayer perceptron

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## 1. Introduction

Chokeberry (*Aronia melanocarpa*) is a berry fruit that naturally grows in North America (Poyraz Engin and Boz, 2023). It was introduced to Russia and various parts of Europe from North America in the early 20th century (Chrubasik et al., 2010). It has been cultivated commercially in countries such as Poland, the Czech Republic, and Germany since the 1950s (Šnebergrová et al., 2014).

Morphologically, *A. melanocarpa* (Michx.) Elliot is a deciduous shrub characterized by a dense, suckering habit, typically reaching a height of 1.2 to 2 meters. Its fruits form mid-July and reach maturity in August-September (Brand, 2010). Thanks to its rich bioactive compounds and antioxidant capacity, it can help to treat metabolic diseases (Jeppsson and Johansson, 2000). It has been shown to positively affect diabetes, cardiovascular diseases, urinary tract inflammation, eye inflammation, and various viral diseases. It also helps prevent some cancer cell proliferation (Poyraz Engin et al., 2018).

Chokeberry cultivation is still relatively new in Türkiye, despite its many health benefits and a growing global market. As more people are interested in cultivating this plant, knowing what it needs to thrive well in diverse climates and soils is becoming more important. Sustainable water management is one of the most significant problems in modern farming, especially in places like Türkiye where water scarcity increases. The General Directorate of State Hydraulic Works (DSİ, 2025) states that, according to the 2021 data, Türkiye uses about 58.41 billion cubic meters of water each year, and 77% of that (45.05 billion $m^3$) is used for irrigation in agriculture. This situation highlights the urgent need to optimize irrigation practices and improve plant resilience to abiotic stresses such as drought and salinity.

Salinity stress is a major abiotic factor limiting plant growth and productivity. It mainly affects the plants in arid and semi-arid regions where soil salinization is progressively increasing due to improper irrigation practices and climate change. Root systems are crucial to a plant's ability to absorb water and nutrients from the soil. It also plays a key role in determining a plant's tolerance to saline conditions. The architecture of the root system, such as total root length, root surface area, diameter, volume, and the number of tips and forks, is a crucial indicator of how plants respond to such stress factors.

In recent years, machine learning (ML) techniques have emerged as powerful tools for modeling complex



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biological systems. Traditional statistical methods often fall short when dealing with highly non-linear, multidimensional datasets typical of plant-environment interactions (Camacho et al., 2018). In contrast, machine learning algorithms such as Random Forest, Support Vector Machines, Gradient Boosting, and Artificial Neural Networks can detect subtle patterns and interactions within large datasets without requiring prior assumptions (Ma et al., 2014; Mahood et al., 2020; Soltis et al., 2020). These models have been successfully used to predict crop yield, classify stress responses, and optimize irrigation and fertilization regimes based on various physiological and morphological parameters (Jeong et al., 2016; Singh, 2016; Van Dijk et al., 2021; Tütüncü, 2024).

Applying machine learning to root architecture analysis under salinity stress offers several advantages. It allows for the accurate prediction of plant responses based on measurable traits. There is a significant lack of comprehensive literature studies that evaluate the root architecture of *A. melanocarpa*.

This study aimed to investigate the effects of salt stress on the root architecture of chokeberry and to model the plant's morphological responses using artificial intelligence machine learning techniques.

## 2. Materials and Methods

The research was conducted in the greenhouse of Samsun Ondokuz Mayıs University, Faculty of Agriculture, between 2021-2022. In the study, 1-year-old plants of 'Viking' chokeberry cultivar were used. The plants were transferred into 15 litter pots and placed on a set 10 cm above the soil level (Figure 1).



**Figure 1.** Experimental setup of *A. melanocarpa* plants grown under controlled greenhouse conditions.

The study was conducted to evaluate the effects of irrigation water quality on plant root development. A control and four different levels of saline irrigation water were applied (0.65 dS $m^{-1}$(control), 2 dS $m^{-1}$, 4 dS $m^{-1}$, 8 dS $m^{-1}$, 10 dS $m^{-1}$). Peat and soil were used as growing mediums for all treatments. The saline solutions were prepared using three different salts. $MgSO_4$ with 99% purity, $CaCl_2$ with 99% purity and NaCl with 99.5% purity with high water solubility were used. The required electrical conductivity (EC) value for each treatment subject was determined in QBASIC computer program so that Sodium Adsorption Ratio (SAR) <5 and Ca/Mg ratio 1/1. The amounts of salt used per 1L of water according to the application subjects are stated in Table 1.

**Table 1.** Amounts of salt used in salt stress (g $L^{-1}$)

| Treatments | NaCl | $MgSO_4$ | $CaCl_2$ |
|---|---|---|---|
| 2 dS $m^{-1}$ | 0.56 | 0.45 | 0.31 |
| 4 dS $m^{-1}$ | 0.87 | 1.75 | 0.75 |
| 8 dS $m^{-1}$ | 1.50 | 5.00 | 1.75 |
| 10 dS $m^{-1}$ | 2.00 | 6.12 | 2.5 |

### 2.1. Assessment of Root Architecture

At the end of the experimental period, the plants were carefully uprooted and removed from the pots in October. The roots were carefully washed and dried with paper towels. They were weighed on a precision balance to determine fresh root weight (g). The roots were then placed on A3 size acetate, and the roots were carefully separated to be detected in detail by the device. The roots, which were prepared for scanning, were placed on the scanner (Epson Expression 10000XL, Epson America Inc., Long Beach, CA, USA) of the device and transferred to the computer environment in three dimensions at 400 dpi resolution. WinRhizo root analysis program (ver. 2013, Regent Instruments, QC, Canada) (Sarıbaş et al. 2019) was used to examine the root architecture. Total root length (cm), root surface area ($cm^2$), root volume ($cm^3$), average root diameter (mm), number of root tips, forks, and crossings parameters of chokeberry plant were examined by WinRhizo root analysis program. After the analysis roots were placed in an oven at 80 $^0$C for 72 hours. When they reached a constant weight, they were weighed to determine the root dry weight (g).

### 2.2. Modeling Procedure

The root architecture of chokeberry plants was predicted using three machine learning (ML) models: a multilayer perceptron (MLP) representing artificial neural networks (ANN), extreme gradient boosting (XGBoost), and Gaussian process regression (GPR). The dataset was randomly split into training (70%) and testing (30%) subsets to evaluate the performance of the machine learning models.

Fresh root weight, dry root weight, total root length, surface area, average diameter, root volume, number of tips, forks, and crossings were each treated as target (dependent) variables in separate models. For each trait, machine learning algorithms including Extreme Gradient Boosting (XGBoost), Multilayer Perceptron (MLP), and Gaussian Process Regression (GPR) were applied using the remaining eight traits as input features. For the MLP model, a feed-forward neural network was implemented with two hidden layers consisting of 16 and 8 neurons,

respectively. The ReLU (Rectified Linear Unit) activation function was used in the hidden layers, while a linear activation function was applied in the output layer. To avoid overfitting, early stopping was applied during the training process. For the XGBoost model, the main hyperparameters were as follows: maximum tree depth (max_depth = 6), learning rate (eta = 0.1), and number of boosting rounds (nrounds = 100). Hyperparameter tuning was carried out using a grid search strategy combined with 5-fold cross-validation, and the best-performing configuration was selected for model evaluation. For the GPR model, the Radial Basis Function (RBF) kernel was employed as the covariance function. Kernel parameters were optimized through cross-validation starting from default values. Although a polynomial kernel was also tested, the RBF kernel provided higher predictive accuracy and was therefore selected as the final kernel function. All machine learning models were implemented using the R programming (version 4.3.3) with the assistance of the "caret", "xgboost", "neuralnet", and "kernlab" packages. For model training and evaluation, each root trait was treated as a separate dependent variable, and the remaining traits were used as predictors. The performance of each model was evaluated using commonly accepted regression metrics. These included the Mean Absolute Error (MAE), the Root Mean Square Error (RMSE), the Coefficient of Determination ($R^2$), and the Mean Absolute Percentage Error (MAPE) (equations 1, 2, 3 and 4).

$$MAE=\frac{1}{n}\sum_{i=1}^{n}|yi-\hat{y}i| \quad (1)$$

$$RMSE=\sqrt{\frac{1}{n}}\sum_{i=1}^{n}(yi-\hat{y}i)2 \quad (2)$$

$$R^2=1\frac{\sum_{i=1}^{n}(yi-\hat{y}i)2}{\sum_{i=1}^{n}(yi-\bar{y}i)2} \quad (3)$$

$$MAPE=\frac{100}{n}\sum_{i=1}^{n}\left|\frac{yi-\hat{y}i}{yi}\right| \quad (4)$$

The experiment was conducted using a randomized plot design with three replications, each consisting of three plants. The experiment was repeated for two years with different plants. For Machine Learning the data of two years were combined and analyzed together. Descriptive analyses were done by using Microsoft Office 2015 Excel package program.

## 3. Results

### 3.1. Evaluation of the Effects of Treatments on Root Development

Descriptive statistics of root fresh weight, root dry weight, root length, root surface area, root volume, average root diameter, root tips, forks and crossings training values are given in Table 2. Root fresh weight (g) was varied between 25.6 g (10 dS $m^{-1}$) and 138.7 g (control) in training data. The highest average root dry weight (40.1 g) was obtained in the control treatment. Root length was varied between 490.2 cm (10 dS $m^{-1}$) and 1942.2 cm (control). Also, surface area was varied between 636.3 $cm^2$ (10 dS $m^{-1}$) and 2439 $cm^2$ (control). The highest average diameter (5.4 mm) and the highest root volume (247.4 $cm^3$) was obtained in the control application. Besides, the highest root tips (5453), forks (25970) and crossing (7135) were obtained from the control application (Table 2).

**Table 2.** Descriptive statistics of training dataset

| | Root Fresh Weight (g) | | | Root Dry Weight (g) | | | Root Length (cm) | | |
|---|---|---|---|---|---|---|---|---|---|
| | Min | Max | Mean±SD | Min | Max | Mean±SD | Min | Max | Mean±SD |
| Control | 66.7 | 138.7 | 103.2±30 | 28.2 | 54.7 | 40.1±10 | 1056.5 | 1942.2 | 1520±357 |
| 2 dS $m^{-1}$ | 57.6 | 127.6 | 88.4±29 | 21.1 | 46.8 | 32.7±10 | 903.9 | 1788.9 | 1336±388 |
| 4 dS $m^{-1}$ | 41.2 | 91.9 | 67.3±19 | 17.1 | 34.2 | 25.3±6.6 | 724.3 | 1462.1 | 1081±322 |
| 8 dS $m^{-1}$ | 33.6 | 65.4 | 45.9±11 | 10.9 | 23.9 | 16.4±4.2 | 666.6 | 1181.3 | 895±194 |
| 10 dS $m^{-1}$ | 25.6 | 43.4 | 34.5±6 | 10.4 | 17.1 | 12.7±1.9 | 490.2 | 1023.3 | 727±202 |
| | Surf Area ($cm^2$) | | | Avgdiam (mm) | | | Root Volume ($cm^3$) | | |
| | Min | Max | Mean±SD | Min | Max | Mean±SD | Min | Max | Mean±SD |
| Control | 1404.2 | 2439.0 | 1934.8±418 | 3.2 | 6.9 | 5.4±1.2 | 219.4 | 268.1 | 247.4±12 |
| 2 dS $m^{-1}$ | 1102.1 | 2083.5 | 1497.1±348 | 3.0 | 6.7 | 4.6±1.4 | 134.7 | 227.1 | 189.6±35 |
| 4 dS $m^{-1}$ | 901.9 | 1785.4 | 1275.7±315 | 2.7 | 6.6 | 4.9±1.4 | 107.7 | 224.7 | 165.1±40 |
| 8 dS $m^{-1}$ | 753.6 | 1465.3 | 1076.8±278 | 2.6 | 6.4 | 4.8±1.2 | 85.9 | 177.6 | 137.1±38 |
| 10 dS $m^{-1}$ | 636.3 | 1081.7 | 878.1±132 | 2.8 | 6.9 | 4.6±1.3 | 63.4 | 155.5 | 111.8±37 |
| | Root Tips | | | Root Forks | | | Root Crossing | | |
| | Min | Max | Mean±SD | Min | Max | Mean±SD | Min | Max | Mean±SD |
| Control | 4060 | 6623 | 5453±877 | 14923 | 39468 | 25970±8412 | 5699 | 8889 | 7135±881 |
| 2 dS $m^{-1}$ | 2348 | 6482 | 4389±932 | 12174 | 27155 | 19033±4329 | 2223 | 5671 | 4361±1038 |
| 4 dS $m^{-1}$ | 2422 | 5047 | 3859±912 | 12786 | 22384 | 17440±3346 | 1784 | 4891 | 3282±1252 |
| 8 dS $m^{-1}$ | 2263 | 4531 | 3237±802 | 10434 | 20315 | 15120±3856 | 1173 | 3546 | 2264±773 |
| 10 dS $m^{-1}$ | 2255 | 3802 | 2824±480 | 10267 | 17796 | 12083±2087 | 1195 | 3115 | 2095±693 |

In the test dataset (Table 3), root fresh weight ranged from 40.3 g (10 dS $m^{-1}$) to 134.6 g (control), while root dry weight ranged from 10.4 g (10 dS $m^{-1}$) to 50.6 g (control). The lowest root length (533.1 cm) was recorded at 10 dS $m^{-1}$, whereas the highest (1809 cm) was recorded in the control treatment. Root surface area values varied between 921.4 $cm^2$ (10 dS $m^{-1}$) and 2139 $cm^2$ (2 dS $m^{-1}$). Average diameter ranged from 2.2 mm (4 dS $m^{-1}$) to 6.9 mm (8 dS $m^{-1}$), while root volume ranged from 65.5 $cm^3$ (10 dS $m^{-1}$) to 231.6 $cm^3$ (control). The highest values for root tips (5827), forks (31,101), and crossings (8150) were also obtained from the control treatment (Table 3).

The descriptive statistic was done according to the years. For this purpose, root fresh weight, root dry weight, root length, root surface area, root volume, average root diameter, root tips, forks and crossings data were determined. In the experiment soil and peat mediums were used. Table 4 presents the results of the descriptive statistical analysis for chokeberry plants grown in soil in 2021.

In 2021 in the soil medium the root fresh weight values were ranged from 30.1 g (10 dS $m^{-1}$) to 81.3 g (control) (Table 4). Dry root weight values ranged from 13.2 g (10 dS $m^{-1}$) to 31.4 g (control), with the highest average value obtained in the control (30.9 g) application. The root length value was highest in the control application (1274.7 cm) and the lowest in the 10 dS $m^{-1}$ irrigation water application (490.2 cm). Like the fresh root weight, dry root weight, and root length values, the root surface area was found to be highest in the control treatment (1623.9 $cm^2$) and lowest in the 10 dS $m^{-1}$ irrigation water treatment (636.3 $cm^2$). The average root diameter value was ranged from 5.00 mm (2 and 10 dS $m^{-1}$) to 6.60 mm (4 dS $m^{-1}$), while the root volume was ranged from 150.1 $cm^3$ (10 dS $m^{-1}$) to 244 $cm^3$ (control). The highest value of the root tips parameter was obtained in the control application (5860), while the lowest was obtained in the 10 dS $m^{-1}$ irrigation water application (2255). The root forks was ranged from 10267 (10 dS $m^{-1}$) to 24111 (control), while the root crossing value ranged from 1173 (8 dS $m^{-1}$) to 7399 (control). The root architecture results of the plants grown in peat medium in 2021 are presented in Table 5.

**Table 3.** Descriptive statistics of testing dataset

| | Root Fresh Weight (g) | | | Root Dry Weight (g) | | | Root Length (cm) | | |
|---|---|---|---|---|---|---|---|---|---|
| | Min | Max | Mean±SD | Min | Max | Mean±SD | Min | Max | Mean±SD |
| Control | 70.0 | 134.6 | 102.3±45 | 31.1 | 50.6 | 40.8±13 | 1217.0 | 1809.0 | 1513±419 |
| 2 dS $m^{-1}$ | 58.1 | 119.5 | 88.7±43 | 23.6 | 44.8 | 34.2±15 | 876.6 | 1756.2 | 1316±621 |
| 4 dS $m^{-1}$ | 42.4 | 91.3 | 62.5±23 | 18.3 | 32.4 | 24.2±7 | 792.3 | 1482.1 | 1117±352 |
| 8 dS $m^{-1}$ | 50.5 | 58.1 | 53.3±40 | 16.1 | 25.6 | 20.1±5 | 658.8 | 1031.9 | 796±205 |
| 10 dS $m^{-1}$ | 40.3 | 42.8 | 41.5±10 | 10.4 | 17.5 | 13.9±5 | 533.1 | 829.6 | 681±209 |
| | Surf Area ($cm^2$) | | | Avgdiam (mm) | | | Root Volume ($cm^3$) | | |
| | Min | Max | Mean±SD | Min | Max | Mean±SD | Min | Max | Mean±SD |
| Control | 1595.1 | 2088.0 | 1841±348 | 3.6 | 5.4 | 4.5±1.2 | 223.4 | 231.6 | 227±5 |
| 2 dS $m^{-1}$ | 1247.3 | 2139.0 | 1693±630 | 4.5 | 5.8 | 5.2±0.9 | 182.9 | 204.8 | 193±15 |
| 4 dS $m^{-1}$ | 970.4 | 1895.2 | 1325±422 | 2.2 | 5.8 | 4.3±1.7 | 108.6 | 192.1 | 162±38.9 |
| 8 dS $m^{-1}$ | 983.4 | 1406.7 | 1136±235 | 3.2 | 6.9 | 5.1±1.8 | 147.7 | 177.4 | 167±16 |
| 10 dS $m^{-1}$ | 921.4 | 944.5 | 933±16 | 3.6 | 4.6 | 4.1±0.7 | 65.5 | 146.7 | 106±57 |
| | Root Tips | | | Root Forks | | | Root Crossing | | |
| | Min | Max | Mean±SD | Min | Max | Mean±SD | Min | Max | Mean±SD |
| Control | 4649 | 5827 | 5238±832 | 18368 | 31101 | 24734±9003 | 5229 | 8150 | 6689±2065 |
| 2 dS $m^{-1}$ | 2563 | 5421 | 3992±202 | 13733 | 22581 | 18157±6256 | 3546 | 4701 | 4123±816 |
| 4 dS $m^{-1}$ | 2842 | 5077 | 3643±1055 | 13252 | 20293 | 18425±3151 | 1780 | 4822 | 3072±1525 |
| 8 dS $m^{-1}$ | 3230 | 5541 | 4148±1226 | 15793 | 21474 | 17849±3148 | 2526 | 2990 | 2740±234 |
| 10 dS $m^{-1}$ | 2916 | 3466 | 3191±388 | 12348 | 13075 | 12711±514 | 1800 | 2851 | 2325±743 |

**Table 4.** Descriptive statistical values of chokeberry plants grown in soil medium in 2021

| | Root Fresh Weight (g) | | | Root Dry Weight (g) | | | Root Length (cm) | | |
|---|---|---|---|---|---|---|---|---|---|
| Soil/2021 | Min | Max | Mean±SD | Min | Max | Mean±SD | Min | Max | Mean±SD |
| Control | 74.5 | 81.3 | 78.9±3.8 | 30.4 | 31.4 | 30.9±0.5 | 1236.3 | 1274.7 | 1255±19.1 |
| 2 dS $m^{-1}$ | 57.6 | 60.7 | 59.5±1.6 | 21.1 | 21.6 | 21.3±0.2 | 945.9 | 1096.7 | 1012.4±76 |
| 4 dS $m^{-1}$ | 41.2 | 43.1 | 42.2±0.9 | 17.1 | 18.3 | 17.9±0.7 | 792.3 | 862.6 | 831.9±35 |
| 8 dS $m^{-1}$ | 33.6 | 36.2 | 34.9±1.3 | 14.7 | 16.0 | 15.2±0.7 | 666.6 | 726.5 | 694.5±30 |
| 10 dS $m^{-1}$ | 30.1 | 30.7 | 30.3±0.3 | 13.2 | 13.7 | 13.4±0.3 | 490.2 | 527.8 | 504.5±20 |
| | Surf Area ($cm^2$) | | | Avgdiam (mm) | | | Root Volume ($cm^3$) | | |
| Soil/2021 | Min | Max | Mean±SD | Min | Max | Mean±SD | Min | Max | Mean±SD |
| Control | 1404.2 | 1623.9 | 1527.7±112.3 | 5.5 | 6.3 | 5.9±0.3 | 242.4 | 244.0 | 243±0.9 |
| 2 dS $m^{-1}$ | 1102.1 | 1260.4 | 1189.9±80.5 | 5.0 | 6.0 | 5.7±0.5 | 203.4 | 227.1 | 218±12.9 |
| 4 dS $m^{-1}$ | 901.9 | 1041.0 | 971.1±69 | 5.7 | 6.6 | 6.1±0.4 | 190.3 | 197.6 | 193±3.7 |
| 8 dS $m^{-1}$ | 753.6 | 788.1 | 768.9±17.6 | 5.6 | 6.4 | 6.1±0.4 | 171.8 | 177.6 | 174±2.8 |
| 10 dS $m^{-1}$ | 636.3 | 745.3 | 701.2±57.3 | 5.0 | 6.4 | 5.6±0.7 | 150.1 | 155.5 | 152±2.8 |
| | Root Tips | | | Root Forks | | | Root Crossing | | |
| Soil/2021 | Min | Max | Mean±SD | Min | Max | Mean±SD | Min | Max | Mean±SD |
| Control | 5451 | 5860 | 5639±206 | 20059 | 24111 | 21472±2287 | 6845 | 7399 | 7162±285 |
| 2 dS $m^{-1}$ | 2348 | 3828 | 3139±745 | 12174 | 16001 | 14706±2193 | 2223 | 4693 | 3645±1276 |
| 4 dS $m^{-1}$ | 2422 | 2856 | 2706±246 | 12786 | 14572 | 13536±926 | 1780 | 1807 | 1790±14.5 |
| 8 dS $m^{-1}$ | 2263 | 2509 | 2426±141 | 10434 | 10909 | 10610±260 | 1173 | 1555 | 1400±201 |
| 10 dS $m^{-1}$ | 2255 | 2636 | 2449±190 | 10267 | 11397 | 10715±599 | 1195 | 1544 | 1341±181 |

**Table 5.** Descriptive statistical values of chokeberry plants grown in peat medium in 2021

| | Root Fresh Weight (g) | | | Root Dry Weight (g) | | | Root Length (cm) | | |
|---|---|---|---|---|---|---|---|---|---|
| Peat/2021 | Min | Max | Mean±SD | Min | Max | Mean±SD | Min | Max | Mean±SD |
| Control | 132.0 | 138.7 | 134±3.6 | 48.7 | 49.1 | 48.9±0.1 | 1838.5 | 1942.2 | 1883±53 |
| 2 dS $m^{-1}$ | 119.5 | 127.6 | 122±4.2 | 44.5 | 46.8 | 45.4±1.2 | 1724.8 | 1788.0 | 1756±31 |
| 4 dS $m^{-1}$ | 91.3 | 91.9 | 91.7±0.3 | 32.4 | 34.2 | 33.1±0.9 | 1438.8 | 1482.0 | 1461±21 |
| 8 dS $m^{-1}$ | 58.1 | 65.4 | 61.4±3.6 | 22.5 | 25.6 | 24±1.5 | 1007.3 | 1031.9 | 1021±12 |
| 10 dS $m^{-1}$ | 25.6 | 30.7 | 28.9±2.8 | 10.5 | 11.7 | 11.2±0.6 | 800.4 | 886.0 | 831±47 |
| | Surf Area ($cm^2$) | | | Avgdiam (mm) | | | Root Volume ($cm^3$) | | |
| Peat/2021 | Min | Max | Mean±SD | Min | Max | Mean+SD | Min | Max | Mean±SD |
| Control | 2318.3 | 2439.0 | 2390.6±63 | 3.2 | 5.8 | 4.6±1.2 | 252.4 | 254.2 | 253±1.0 |
| 2 dS $m^{-1}$ | 2051.0 | 2139.0 | 2091.2±44.4 | 3.0 | 4.5 | 3.7±0.7 | 202.7 | 207.6 | 205±2.4 |
| 4 dS $m^{-1}$ | 1682.9 | 1895.2 | 1787.8±106 | 3.0 | 4.9 | 3.8±1.0 | 160.4 | 172.7 | 167±6.2 |
| 8 dS $m^{-1}$ | 1406.7 | 1465.3 | 1439.9±30 | 3.2 | 4.5 | 3.9±0.6 | 141.8 | 147.7 | 145.2±3 |
| 10 dS $m^{-1}$ | 963.0 | 1081.7 | 1016.3±60 | 3.5 | 4.6 | 4.1±0.5 | 90.1 | 102.5 | 96.1±6.2 |
| | Root Tips | | | Root Forks | | | Root Crossing | | |
| Peat/2021 | Min | Max | Mean±SD | Min | Max | Mean±SD | Min | Max | Mean±SD |
| Control | 5837 | 6288 | 6035±238 | 28016 | 39468 | 35551±6527 | 7412 | 8889 | 7936±826 |
| 2 dS $m^{-1}$ | 5421 | 6482 | 5921.6±533 | 22388 | 27155 | 24041±2698 | 4701 | 5671 | 5265±504 |
| 4 dS $m^{-1}$ | 5018 | 5077 | 5047.3±29.5 | 20293 | 22384 | 21290±1048 | 4757 | 4891 | 4823±67 |
| 8 dS $m^{-1}$ | 4167 | 5541 | 4746±711 | 19182 | 21474 | 20323±146 | 2705 | 3546 | 3112±421 |
| 10 dS $m^{-1}$ | 2430 | 3246 | 2733±446 | 10627 | 13150 | 11640±1332 | 2016 | 2916 | 2409±460 |

The root fresh weight was ranged from 25.6 g (10 dS $m^{-1}$) to 138.7 g (control), while root dry weight was ranged from 10.5 g (10 dS $m^{-1}$) to 49.1 g (control). In both fresh and dry root weight parameters, increasing salinity levels led to a noticeable reduction in root weight. Increasing salinity levels resulted in a progressive decline in root length. In the control application, root length was measured as 1942.2 cm, while in the 10 dS $m^{-1}$ salt application, it was measured as 800.4 cm. On the other hand, root area ranged from 963 $cm^2$ (10 dS $m^{-1}$) to 2439 $cm^2$ (control), while root volume ranged from 90.1 $cm^3$ (10 dS $m^{-1}$) to 254.2 $cm^3$ (control). Both parameters exhibited a declining trend as salt concentration increased. The average root diameter was lowest at 2 and 4 dS $m^{-1}$ salinity levels (3.0 mm), while the highest value was observed in the control treatment (5.8 mm). Root tips, forks, and crossing values showed a decreasing trend with increasing irrigation water salinity. The highest values for all three parameters were obtained in the control application, while the lowest values were obtained in the 10 dS $m^{-1}$ irrigation water application (Table 5).

The descriptive statistical values of the analysis results from the second year of the experiment are presented in soil medium (Table 6) and peat medium (Table 7).

In 2022, in the soil medium, the root fresh weight was ranged from 42.8 g (10 dS $m^{-1}$) to 70 g (control) (Table 6), while in the peat medium it was ranged from 36.8 g (10 dS $m^{-1}$) to 134.6 g (control) (Table 7). Similar to the observations in 2021, root dry weight decreased with increasing salt concentrations in both peat and soil growing media, with the lowest value recorded at 10 dS $m^{-1}$. The average dry root weight was determined to be 29.6 g in the soil medium and 51.5 g in the peat medium. Root length values were ranged from 533.1 cm (10 dS $m^{-1}$) to 1217.2 cm (control) in the soil environment and from 829.6 cm (10 dS $m^{-1}$) to 1882 cm (control) in the peat environment. Root surface area and root volume values decreased with increasing salt concentration in both peat and soil mediums. The average root surface area was recorded as 1590.8 $cm^2$ in the soil and 2336.4 $cm^2$ in the peat medium. The average root volume was measured as 249.1 $cm^3$ in the soil and 231.2 $cm^3$ in the peat medium. The average root diameter value ranged from 4.60 to 6.90 mm in the soil and from 2.20 to 4.80 mm in the peat medium. Root tips, forks, and crossing values decreased with increasing salt levels in both peat and soil mediums. Root tips were determined as a maximum of 4649 (control) in the soil and 6623 (control) in the peat mediums. The average maximum values of the root forks were obtained from the control application in both growing mediums. Root crossing values ranged from 1523 (10 dS $m^{-1}$) to 6011 (control) in soil and from 2150 (8 dS $m^{-1}$) to 8150 (control) in peat.

**Table 6.** Descriptive statistical values of chokeberry plants grown in soil medium in 2022

| | Root Fresh Weight (g) | | | Root Dry Weight (g) | | | Root Length (cm) | | |
|---|---|---|---|---|---|---|---|---|---|
| Soil/2022 | Min | Max | Mean±SD | Min | Max | Mean±SD | Min | Max | Mean±SD |
| Control | 66.7 | 70.0 | 68.6±1.6 | 28.2 | 31.1 | 29.6±1.4 | 1056.5 | 1217.2 | 1134.6±80 |
| 2 dS $m^{-1}$ | 58.0 | 65.4 | 61.1±3.8 | 22.4 | 26.8 | 24.2±2.2 | 876.6 | 939.9 | 906.8±31 |
| 4 dS $m^{-1}$ | 52.7 | 53.3 | 53±0.3 | 18.5 | 21.9 | 20.4±1.7 | 724.3 | 785.4 | 761.2±32 |
| 8 dS $m^{-1}$ | 48.4 | 51.3 | 50.1±1.4 | 16.2 | 18.5 | 17.3±1.1 | 658.8 | 710.5 | 688.9±26 |
| 10 dS $m^{-1}$ | 42.8 | 43.3 | 43.1±0.3 | 14.7 | 17.5 | 16.4±1.5 | 533.1 | 586.8 | 557±27 |
| | Surf Area ($cm^2$) | | | Avgdiam (mm) | | | Root Volume ($cm^3$) | | |
| Soil/2022 | Min | Max | Mean±SD | Min | Max | Mean±SD | Min | Max | Mean±SD |
| Control | 1545.4 | 1632.1 | 1590.8±43 | 5.4 | 6.9 | 6.4±0.8 | 223.4 | 268.1 | 249.1±23 |
| 2 dS $m^{-1}$ | 1247.3 | 1277.9 | 1260.3±15 | 5.8 | 6.7 | 6.1±0.4 | 182.9 | 215.1 | 189±16 |
| 4 dS $m^{-1}$ | 1020.1 | 1146.4 | 1082.6±63 | 5.0 | 6.5 | 5.8±0.7 | 165.4 | 224.7 | 189.1±31 |
| 8 dS $m^{-1}$ | 953.3 | 1018.1 | 984.9±32 | 5.3 | 6.9 | 5.9±0.8 | 154.7 | 177.4 | 169.4±12 |
| 10 dS $m^{-1}$ | 856.8 | 921.4 | 879.5±36 | 4.6 | 6.9 | 5.4±1.2 | 142.5 | 146.7 | 143.9±2.3 |
| | Root Tips | | | Root Forks | | | Root Crossing | | |
| Soil/2022 | Min | Max | Mean±SD | Min | Max | Mean±SD | Min | Max | Mean±SD |
| Control | 4060 | 4649 | 4281±320 | 14923 | 18661 | 17317±2078 | 5229 | 6011 | 5646±393 |
| 2 dS $m^{-1}$ | 2563 | 3835 | 3328±674 | 13733 | 17794 | 15871±2039 | 3546 | 4499 | 3958±489 |
| 4 dS $m^{-1}$ | 2954 | 3704 | 3422±408 | 15103 | 15362 | 15222±130 | 1875 | 2878 | 2397±502 |
| 8 dS $m^{-1}$ | 3006 | 3674 | 3303±339 | 13972 | 16281 | 15348±1216 | 2455 | 2990 | 2657±290 |
| 10 dS $m^{-1}$ | 2708 | 2916 | 2783±115 | 11464 | 13075 | 12180±820 | 1523 | 1800 | 1682±143 |

The findings of this study show that increasing salinity levels significantly negatively affect root morphology parameters in *A. melanocarpa*. All root growth indicators, such as total root length, surface area, root volume, average root diameter, and root tip number, decreased significantly with increasing salt concentration. Similarly, the literature widely reports that salt stress inhibits plant root development. For example, a study on the chokeberry indicated that increasing salt concentration progressively reduced plant height, fresh/dry weight, and root length (Mahmood and Pırlak, 2025). Similarly, it is stated that salinity negatively affects both the above-ground and root system growth of apple rootstock seedlings, causing a significant decrease in root length and biomass (Li et al., 2024). The general scientific consensus is that plants under salt stress show significant declines in morphological indicators. In particular, salt damages the roots results in a reduction in root length and mass (Li et al., 2024). Studies conducted on the model plants *Arabidopsis thaliana*, rice, and soybeans have shown that both main root length and lateral root formation are significantly inhibited in the presence of salt (Liu et al., 2025). Additionally, high salt concentrations have been reported to seriously affect root architecture in species such as corn, wheat, and apple (Rahnama et al., 2011; Li et al., 2021; Li et al., 2024). Indeed, salt stress in wheat seedlings significantly reduced total root length and root surface area, while also decreasing root biomass and weakening overall root development. In a study where 0, 50, 100, and 150 mM NaCl was applied to 'Viking' chokebery plants in MS and semi-MS media, it was determined that root length, root age, and dry weight decreased with increasing salt concentrations (Nas et al., 2025). Bryla and Scagel (2014) stated that the root weight of the 'Honeoye' strawberry variety that is treated with $CaCl_2$ decreased by 19-48% due to salt stress. Also, in another study conducted with strawberries, 35 mM NaCl salt dose reduced root volume by 37% (Aras and Eşitgen, 2018). This study also shows that the chokeberry root system is extremely sensitive to salt, and that salinity causes a decline in all root architecture parameters, which is consistent with the general findings in the literature.

### 3.2. Analysis of ML Models

The data obtained from the root architecture analysis of chokeberry plants grown under different irrigation qualities were analyzed using artificial neural network-based multilayer perceptron (MLP), XGBoost, and GPR machine learning algorithms. The results were validated and estimated using performance metrics such as root mean square error (RMSE), the coefficient of determination ($R^2$), mean absolute error (MAE) and mean absolute percentage error (MAPE) The changes in the modeled algorithms according to irrigation applications are presented in Table 8.

**Table 7.** Descriptive statistical values of chokeberry plants grown in peat medium in 2022

| | Root Fresh Weight (g) | | | Root Dry Weight (g) | | | Root Length (cm) | | |
|---|---|---|---|---|---|---|---|---|---|
| Peat/2022 | Min | Max | Mean±SD | Min | Max | Mean±SD | Min | Max | Mean±SD |
| Control | 124.9 | 134.6 | 130.3±4.9 | 49.4 | 54.7 | 51.5±2.7 | 1715 | 1882 | 1802±84 |
| 2 dS m$^{-1}$ | 108.3 | 112.1 | 110.4±1.9 | 38.8 | 42.8 | 40.9±2.0 | 1570 | 1788 | 1655±116 |
| 4 dS m$^{-1}$ | 73.1 | 78.5 | 75.7±2.7 | 27.0 | 30.2 | 28.3±1.6 | 1298 | 1356 | 1321±31 |
| 8 dS m$^{-1}$ | 41.3 | 47.7 | 44.5±3.2 | 10.9 | 14.2 | 12.9±1.8 | 996 | 1181 | 1075±95 |
| 10 dS m$^{-1}$ | 36.8 | 40.3 | 38.4±1.7 | 10.4 | 12.2 | 11.3±0.9 | 829.6 | 1023.3 | 950±105 |
| | Surf Area (cm$^2$) | | | Avgdiam (mm) | | | Root Volume (cm$^3$) | | |
| Peat/2022 | Min | Max | Mean±SD | Min | Max | Mean±SD | Min | Max | Mean±SD |
| Control | 2079.5 | 2336.4 | 2167±145 | 3.6 | 4.7 | 4.1±0.5 | 219.4 | 242.5 | 231.2±11 |
| 2 dS m$^{-1}$ | 1486.8 | 1692.1 | 1577±104 | 3.2 | 3.6 | 3.4±0.1 | 134.7 | 147.3 | 139.9±6.5 |
| 4 dS m$^{-1}$ | 1227 | 1395 | 1327±88 | 2.2 | 4.8 | 3.2±1.3 | 107.7 | 108.6 | 108.1±0.4 |
| 8 dS m$^{-1}$ | 1118 | 1210 | 1172±48 | 2.6 | 4.2 | 3.5±0.7 | 85.9 | 90.6 | 88.9±2.6 |
| 10 dS m$^{-1}$ | 903.1 | 944.5 | 929±23 | 2.8 | 3.6 | 3.1±0.4 | 63.4 | 70.6 | 66.5±3.7 |
| | Root Tips | | | Root Forks | | | Root Crossing | | |
| Peat/2022 | Min | Max | Mean±SD | Min | Max | Mean±SD | Min | Max | Mean±SD |
| Control | 4694 | 6623 | 5714±969 | 24001 | 31101 | 28718±4085 | 6850 | 8150 | 7499±650 |
| 2 dS m$^{-1}$ | 4346 | 5972 | 4905±924 | 19601 | 22599 | 20930±1527 | 3521 | 5385 | 4418±933 |
| 4 dS m$^{-1}$ | 3800 | 4178 | 3873±190 | 17583 | 18837 | 18357±677 | 3298 | 4337 | 3838±520 |
| 8 dS m$^{-1}$ | 3028 | 3949 | 3385±493 | 15805 | 18293 | 16929±1261 | 2150 | 2543 | 2362±198 |
| 10 dS m$^{-1}$ | 2820 | 3802 | 3382±499 | 12241 | 17796 | 14128±3176 | 2586 | 3115 | 2850±264 |

**Table 8.** Performance metrics of MLP, XGBoost, and GPR Models for root trait prediction

| Parameters | MLP and ML Models | $R^2$ | RMSE | MAE | MAPE (%) |
|---|---|---|---|---|---|
| Fresh Weight (g) | XGBoost | 0.98 | 4.83 | 3.76 | 7.04 |
| | MLP | 0.98 | 4.98 | 4.16 | 8.57 |
| | GPR | 0.97 | 6.38 | 5.57 | 10.96 |
| Dry Weight (g) | XGBoost | 0.98 | 1.64 | 1.31 | 5.52 |
| | MLP | 0.97 | 2.17 | 1.83 | 7.52 |
| | GPR | 0.97 | 2.26 | 2.05 | 9.01 |
| Length (cm) | XGBoost | 0.95 | 97.97 | 67.13 | 9.24 |
| | MLP | 0.96 | 85.40 | 79.10 | 8.91 |
| | GPR | 0.96 | 86.48 | 76.39 | 9.25 |
| Surface Area ($cm^2$) | XGBoost | 0.92 | 135.54 | 90.73 | 7.01 |
| | MLP | 0.95 | 106.62 | 84.13 | 6.33 |
| | GPR | 0.91 | 171.10 | 131.56 | 9.61 |
| Average Diameter (mm) | XGBoost | 0.76 | 0.63 | 0.56 | 13.23 |
| | MLP | 0.69 | 0.74 | 0.62 | 13.26 |
| | GPR | 0.70 | 0.80 | 0.69 | 15.86 |
| Root Volume ($cm^3$) | XGBoost | 0.83 | 25.20 | 18.53 | 12.72 |
| | MLP | 0.77 | 28.14 | 18.08 | 11.23 |
| | GPR | 0.79 | 28.75 | 22.09 | 14.75 |
| Root Tips | XGBoost | 0.90 | 448.23 | 383.41 | 9.60 |
| | MLP | 0.92 | 353.86 | 274.05 | 7.01 |
| | GPR | 0.87 | 531.00 | 413.06 | 9.84 |
| Root Forks | XGBoost | 0.93 | 2910.56 | 1690.23 | 7.09 |
| | MLP | 0.92 | 2888.59 | 1720.21 | 7.21 |
| | GPR | 0.88 | 3901.71 | 2113.70 | 8.20 |
| Root Crossing | XGBoost | 0.86 | 768.15 | 638.36 | 19.50 |
| | MLP | 0.83 | 874.05 | 689.89 | 19.98 |
| | GPR | 0.78 | 983.29 | 831.60 | 22.90 |

Based on the findings, it was observed that the models generally demonstrated high prediction accuracy ($R^2$ > 0.9). Among the models, XGBoost outperformed both MLP and GPR in many parameters. Although the MLP and GPR models exhibited similar $R^2$ values. However, the MLP model provided better results due to its lower error rates compared to GPR. When the machine learning models were evaluated based on individual parameters, differences were observed among them (Table 8). The fresh root weight parameter was predicted with 98% accuracy by both XGBoost and MLP models. With the lowest error (RMSE: 4.83), XGBoost can be considered the most successful model for predicting fresh root weight. For the dry root weight parameter, the MLP and GPR models achieved 97% accuracy, while the XGBoost model reached 98%, again showing the best performance with lower error values.

Both the MLP and GPR models predicted the root length parameter with high performance, achieving 96% accuracy. The root surface area parameter was predicted by the MLP model with 95% accuracy. The root surface area predicted by the MLP model had an RMSE value of 106.62, while the XGBoost and GPR models achieved $R^2$ values of 0.92 and 0.91, respectively. Regarding the prediction of average diameter and root volume, the XGBoost model showed the highest performance with $R^2$ values of 0.76 and 0.83, respectively. For the root tips parameter, the MLP model performed best with an $R^2$ value of 0.92.

In the prediction of root forks, $R^2$ values ranged between 0.88 and 0.93, with the highest performance obtained from the XGBoost model (0.93). Similarly, in the prediction of the root crossing parameter, the XGBoost model again showed the best performance with 86% accuracy. However, due to MAPE values exceeding 10% for the average diameter, root volume, and root crossing parameters, the prediction accuracy for these traits is considered low. Therefore, the models may not be suitable for accurately predicting these specific parameters.

The literature emphasizes that XGBoost performs particularly well with tabular data and is considered the "default powerful model" for many problems (Gill et al., 2022). Similarly, Duarte et al. (2022) reported that the SVM model performed best in predicting root architecture in 100 different soybean genotypes under two different water conditions, and that the MLP, RF, and XGBoost models also provided more successful results compared to linear models.

Since the data size in our study was relatively limited, MLP was used with a moderately complex architecture and was successful in certain parameters. Indeed, in the study by Aasim et al. (2023), which modeled the response of chickpea seeds to salt stress, it was noted

that the MLP model could predict all germination and growth indices with high accuracy, thereby achieving a level of prediction success that could not be achieved with classical statistical approaches. In a study conducted by Tütüncü (2024), the root architecture of Primula plants was analyzed, and it was reported that the MLP model performed better than other models. While the study clearly showed the order MLP > GP > RF > XGBoost, this study emphasized the superiority of the XGBoost model. This difference may be due to various factors such as plant type, the level of optimization of model parameters, and the content of input variables.

In our study, the underperformance of GPR may have been due to the limited size of the dataset and the difficulty of modeling the relationship between root parameters and salt stress with a single global Gaussian kernel. Similarly, in Dong et al. (2023) sunflower root modeling study, GPR lagged RF and XGBoost; the researchers noted that RF and XGBoost made RLD (root length density) predictions with lower error than GPR.

Figures 2, 3, and 4 illustrate the comparative distributions of observed and machine learning-predicted values for key root architecture traits of chokeberry plants subjected to varying irrigation water salinity levels.

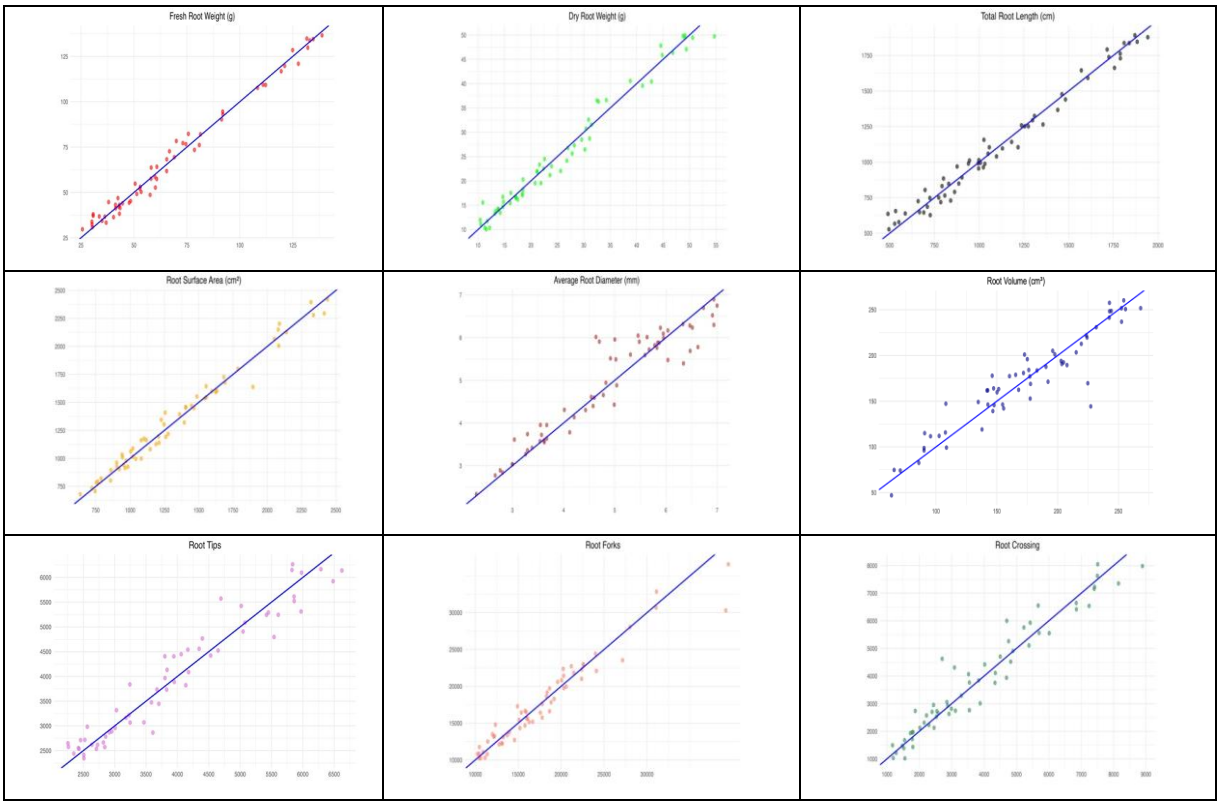



**Figure 2.** Observed and predicted values of the parameters using MLP model.

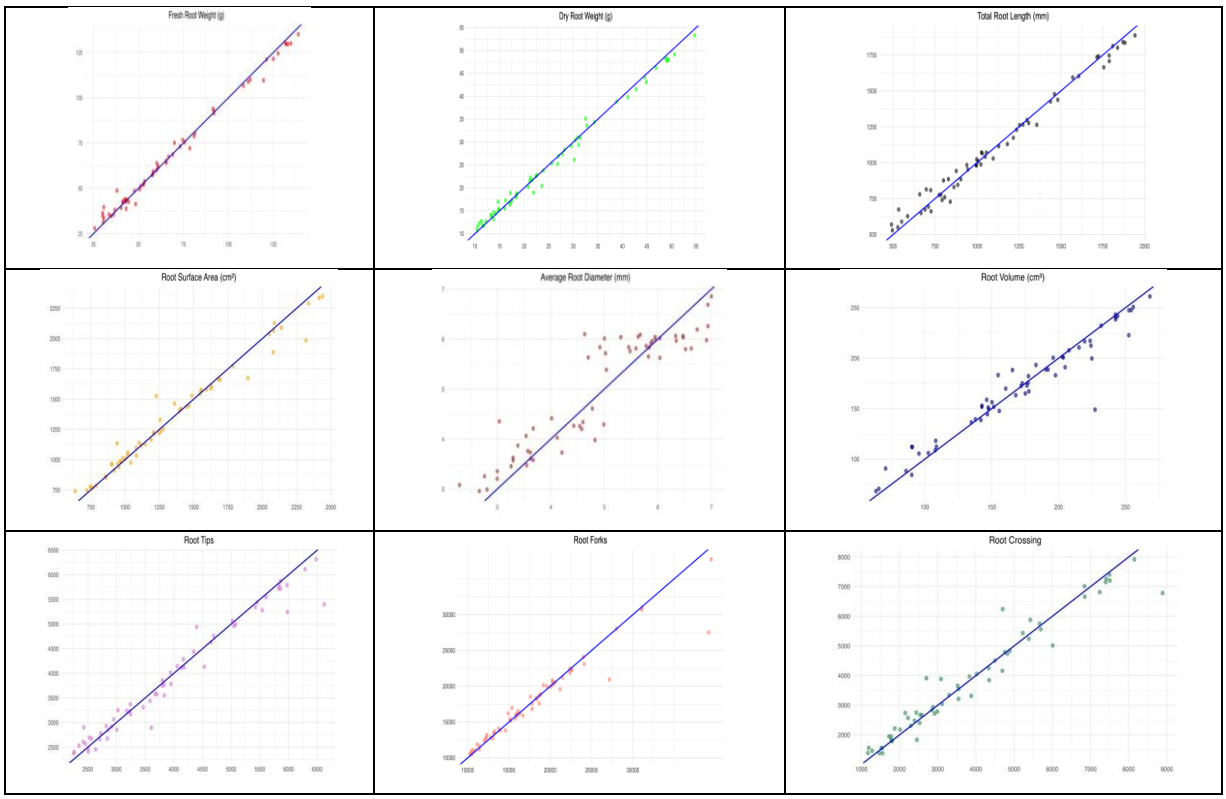



**Figure 3.** Observed and predicted values of the parameters using GPR model.

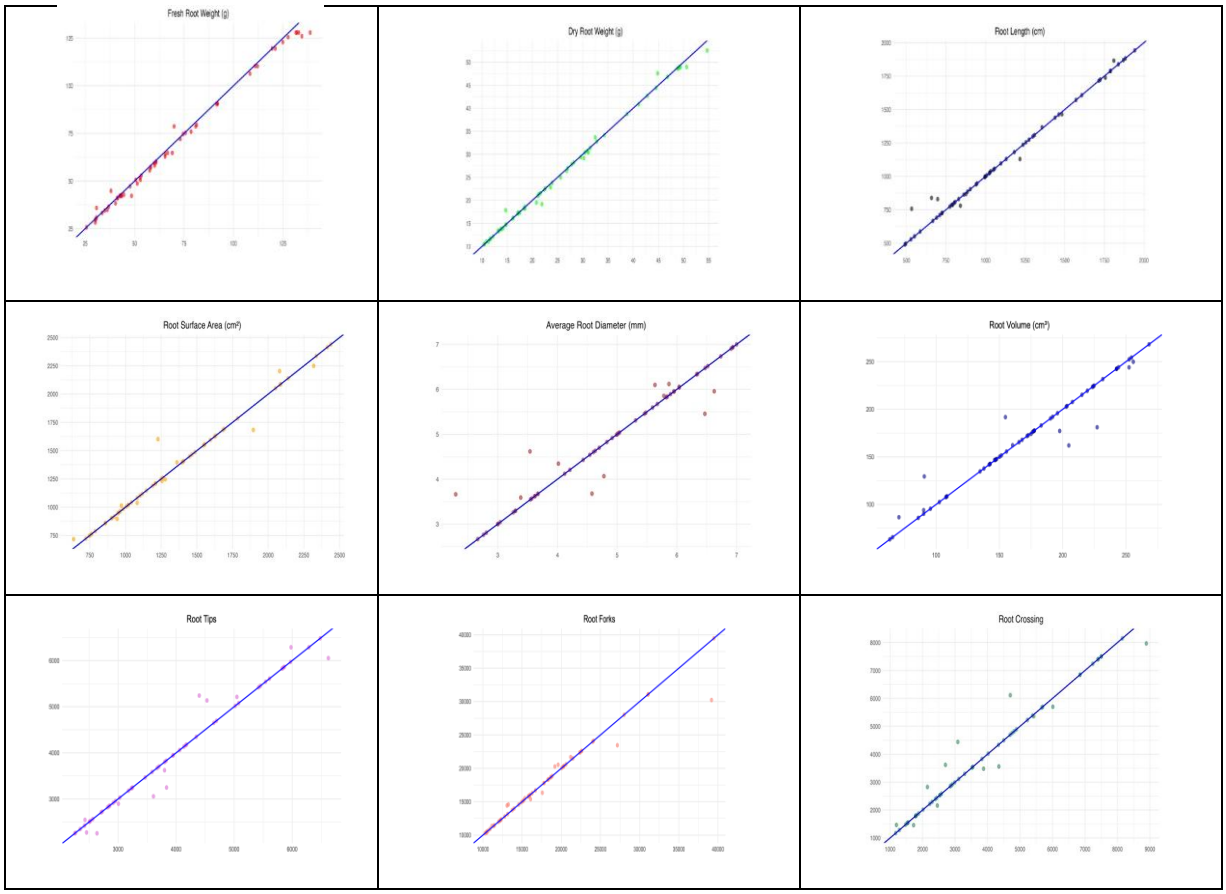



**Figure 4.** Observed and predicted values of the parameters using XGBoost model.

## 4. Conclusion

This study demonstrated that salt stress has a significant adverse impact on the root architecture of chokeberry. As salinity levels increased, reductions were observed in all major root traits, including root length, surface area, volume, average diameter, and biomass. These morphological responses were consistent across both soil and peat growing medium and aligned with existing literature on salinity-induced root inhibition in various horticultural species.

Importantly, this study also confirmed that machine learning techniques, particularly XGBoost and MLP, can effectively model and predict root responses under varying levels of salt stress. Among the tested models, XGBoost demonstrated the highest predictive performance for most traits. In contrast, GPR showed relatively lower accuracy, possibly due to its sensitivity to smaller dataset sizes and kernel limitations.

Overall, this study contributes novel insights into the interaction between salinity stress and chokeberry root architecture and offers a practical modeling framework that can be adapted for similar stress studies in other crops.

**Author Contributions**

The percentages of the authors' contributions are presented below. All author reviewed and approved the final version of the manuscript.

| | A.A. | B.C. |
|---|---|---|
| C | 50 | 50 |
| D | 50 | 50 |
| S | 50 | 50 |
| DCP | 50 | 50 |
| DAI | 50 | 50 |
| L | 50 | 50 |
| W | 50 | 50 |
| CR | 50 | 50 |
| SR | 50 | 50 |
| PM | 50 | 50 |
| FA | 50 | 50 |

C=Concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, CR= critical review, SR= submission and revision, PM= project management, FA= funding acquisition.

**Conflict of Interest**

The authors declared that there is no conflict of interest.

**Ethical Consideration**

Since no studies involving humans or animals were conducted, ethical committee approval was not required for this study.

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