

RESEARCH ARTICLE

Improving Robot Performance through Machine Learning–Based Battery Voltage Estimation

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ABSTRACT: This research explores the intersection of artificial intelligence and robotics, focusing on integrating machine learning for predictive modeling in robotic systems. Specifically, it explores the use of four regression algorithms, decision tree, random forest, Ada boost, and XG boost, to predict battery voltage based on key operational parameters such as joint angles, motor torque, sensor latency, and end-of-performance error. A dataset of 20 observations was used to analyze performance and find relationships between mechanical factors and power efficiency. The analysis found strong correlations between end-of-performance error and motor torque (0.97), joint angle 1 (0.93), and sensor latency (0.89), while showing a strong negative correlation with battery voltage (-0.95). The performance evaluation revealed distinct patterns across the models. Decision tree regression achieved perfect accuracy on the training data ($R^2 = 1.0000$) but underperformed on the test data ($R^2 = 0.8040$), indicating overfitting. Random Forest provided the best overall performance, with a strong training score ($R^2 = 0.9742$) and the highest generalization on the test data ($R^2 = 0.8553$). AdaBoost performed well on training ($R^2 = 0.9986$) but showed moderate test accuracy ($R^2 = 0.7666$). XG Boost matched the decision tree on training accuracy ($R^2 = 1.0000$) but struggled with generalization ($R^2 = 0.6570$), indicating significant overfitting. This study underscores the critical role of battery voltage monitoring in robotic systems, as power fluctuations directly affect position accuracy and overall system reliability. The findings suggest that ensemble models, especially Random Forest, offer a more stable balance between accuracy and generalization, making them suitable for real-time predictive maintenance and system optimization in robotics.

Keywords: Robotics, Machine Learning, Regression Analysis, Battery Voltage Prediction, Random Forest, XG Boost, AdaBoost, Decision Tree, Predictive Modeling, Computer Performance.

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1. INTRODUCTION

Historically, artificial intelligence and robotics have evolved along distinct paths – AI emphasizes abstract reasoning and data-driven learning, while robotics focuses on physical simulation and sensorimotor functions. However, over time, these fields have increasingly converged, leading to the emergence of simulated AI systems that can perceive, reason, and act within complex, real-world environments [1]. The fusion of AI and robotics holds great potential for enhancing autonomous capabilities. AI techniques empower robots to make decisions, learn from experience, and adapt to changing

environments. This synergy has fueled advances in areas such as self-driving cars, home care assistant robots, and smart manufacturing systems. Such systems integrate perception (through vision or tactile perception), cognitive processes (such as planning and decision-making), and physical interaction with their environment in real time [2]. However, challenges remain. The persistent divide between AI and robotics in the academic training and research communities is a significant obstacle. Academic programs, conferences, and publications often treat the two fields separately, which limits innovation across disciplines. Bridging this divide will require shared approaches, collaborative platforms, and integrated academic curricula to equip future researchers with a holistic perspective [3]. One of the most important applications of robotics is in education. Robotics provides hands-on learning opportunities that increase student engagement, improve critical thinking, and enhance

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problem-solving skills. Systematic reviews show that when robotics is integrated into school subjects, it can greatly improve learning outcomes [4]. Robotics is used to teach subjects such as math, science, programming, and engineering, often through interactive platforms such as LEGO Mindstorms. These tools help students connect abstract concepts with real-world applications – for example, understanding geometry through robot movements or understanding coding principles through programming commands [5]. Beyond STEM subjects, robotics is increasingly being used in secondary settings, where students explore storytelling, music, and art through robotic technology. This broadens the appeal of robotics and engages students who may not initially be drawn to technology. The effectiveness of robotics in education depends on using it as a tool to teach broader concepts rather than focusing on robotics as the primary goal [6]. However, a common criticism is the lack of rigorous empirical research evaluating the actual effectiveness of robotics in classroom settings. Many existing programs rely on anecdotal or descriptive evidence.

Going forward, research should use robust experimental designs, including control groups and longitudinal studies, to conclusively demonstrate the educational benefits of robotics in a variety of learning contexts [7, 8]. Beyond the fields of engineering and education, robotics is playing an increasingly important role in the biological sciences, particularly in the study of animal behavior. This field, known as “bio robotics,” involves using robotic systems to simulate and test theories about how animals perceive, learn from, and respond to environmental stimuli. For example, robots designed to mimic insect navigation, using techniques such as optical flow algorithms, are providing valuable insights into behaviors such as how bees avoid obstacles or how crickets use acoustic signals to find mates. These robots serve not only as imitations, but also as testbeds that help confirm or refute biological hypotheses. They require precise model definitions and enable behavioral testing in real-world conditions, complementing traditional simulations and mathematical approaches [9-11]. This approach advances our understanding of how animals integrate sensory input with motor actions and process neural information. It also allows researchers to examine whether interactions with the environment alone can explain behavior, supporting a minimalist view of animal cognition [12-15]. However, it is very important to critically assess the reliability of robotic models. Incorrect representations of an animal's sensory systems or behaviors can lead to erroneous conclusions. Therefore, close collaboration between engineers and biologists is crucial to ensure that these robotic models are biologically accurate and experimentally sound [16-18].

The recent development of deep learning has profoundly impacted robotics. Neural networks have empowered robots to tackle complex cognitive tasks such as object recognition, scene analysis, and motion planning. However, applying deep learning to robotic systems also presents unique challenges. The “reality gap” between simulated training environments and real-world operation is a major challenge.

While simulations provide scalable and controlled settings for training, it is still difficult to transfer learned principles to physical robots [19-21]. Approaches such as domain adaptation and sim-to-real transfer are being developed to bridge this gap. In addition, deep learning in robotics needs to extend beyond perception to combine reasoning and physical metaphor. For example, a robot might need to realize that repositioning an object can improve its view of another object, or that its actions are subject to physical constraints. Achieving such intelligent behavior often requires hybrid approaches that blend data-driven learning with model-based planning and control. Accurately assessing uncertainty and recognizing new or unknown situations (open-set recognition) are critical for safe use in real-world environments. Robots need to be able to recognize and adjust to unfamiliar situations when they are encountered. Techniques such as active learning and continuous learning are currently being explored to address these challenges.

2. EXPERIMENTAL DETAILS

Decision tree regression is the most basic of the four algorithms. It works by repeatedly dividing a dataset into small subsets and assigning a fixed prediction value to each subset. These partitions are made using features that reduce errors very effectively, such as the mean square error (MSE). The main advantages of decision trees are their simplicity and clarity, which make them suitable for applications that require model transparency [22, 23]. Despite their simplicity of interpretation, decision trees can be particularly susceptible to overfitting, especially when the tree becomes too deep and begins to model random noise instead of meaningful patterns. As a result, their accuracy can decrease when applied to small datasets or those with high variability. Strategies such as pruning or limiting tree depth are commonly used to reduce overfitting, but a single decision tree may still lack the consistency needed for critical predictive tasks.

To overcome the weaknesses of individual trees, random forest regression uses an ensemble strategy that creates multiple decision trees and averages their predictions. Each tree is trained on a random subset of the data (a bootstrapped sample) and is based on a random selection of features from each split within the tree. This approach reduces the correlation between trees and strengthens the model's ability to generalize to unseen data. The final prediction is usually the average of all tree outputs. Random forests are known for their high predictive accuracy and resilience to outliers and overfitting. However, this ensemble strategy reduces model interpretation and requires more computational resources, especially when dealing with a large number of trees. Despite this, random forests are widely preferred in practice for their robustness and robust performance in various regression tasks.

Random forests take a different approach by focusing on boosting through sequential learning. Unlike random forests, which train trees in parallel, Ada boost builds them in

sequence, where each new tree is designed to correct the errors of the previous one [23, 24]. This is done by assigning more weight to mis predicted data points, which forces the model to focus more on these difficult cases in subsequent iterations. Ada boost typically uses simple base learners, often shallow trees called decision stumps, that, when combined, form a powerful regression. The main advantages of this algorithm lie in its flexibility and improved performance on noisy datasets. However, it can be more sensitive to outliers, as it tends to emphasize data points that contain noise, which can negatively impact performance.

Extending the boosting concept, XG Boost regression (extreme gradient boosting) is a highly efficient and scalable implementation of gradient boosting. Like AdaBoost, it builds trees sequentially, but uses gradient descent to reduce the loss function in a more refined manner. XG Boost includes features such as regularization to prevent overfitting, parallel processing for faster computation, and advanced tree pruning techniques. It also includes options such as summarization (adjusting the learning rate), row subsampling, and column sampling, all of which contribute to improved generalization. These improvements make XG Boost particularly useful for large datasets and complex, high-dimensional tasks. It is a frequently chosen model in data science competitions due to its high accuracy. However, the complexity of XG Boost requires careful tuning of a large number of hyperparameters, making it more difficult to optimize compared to simpler models [25].

Battery voltage refers to the electrical potential difference between a battery's positive and negative terminals. It is typically measured in volts (V) and indicates the energy per unit charge available from the battery to power a device. The nominal voltage depends on the battery's chemistry, for example, a standard alkaline cell has about 1.5 V, while lithium-ion batteries commonly have around 3.6 to 3.7 V per cell. Battery voltage can fluctuate based on factors such as charge level, load, temperature, and age. Monitoring voltage is crucial for ensuring safe operation, estimating remaining capacity, and optimizing battery performance in applications ranging from electronics to electric vehicles.

3. RESULTS AND DISCUSSION

Table 1 summarizes the descriptive statistics for six important variables in a robotic or mechatronic system: joint angle 1, joint angle 2, motor torque, sensor delay, battery voltage, and end-effector error. Each parameter is based on a dataset of 20 measurements. Joint angle 1 and joint angle 2 show significant variability. Joint angle 1 ranges from 20.0° to 95.0° with an average of 58.25° and 22.42° standard deviations, while joint angle 2 ranges from 25.0° to 90.0° with an average of 58.45° and 18.97° standard deviations. This wide range indicates that robotic joints can cover a wide range of motion that can meet a variety of functional requirements. In contrast, motor torque shows a more concentrated distribution. The torque values range from 1.00 Nm to 2.20 Nm, with a mean of 1.50 Nm and a standard deviation of 0.36 Nm, indicating that the mechanical load applied throughout the system operation is relatively constant. The sensor latency averages 11.2 milliseconds, varying from 7.0 MS to 16.0 MS, and the standard deviation is 2.76 MS. This spread indicates some variability in response time, which may affect the performance of real-time system feedback [26]. The battery voltage shows minimal fluctuation, averaging 23.79 V with a standard deviation of 0.92 V. The narrow range between 22.3 V and 25.1 V indicates that the power supply is well maintained and consistent during use.

Table 2 outlines the evaluation metrics for the AdaBoost regression model used to predict battery voltage (V), showing results from both the training and testing phases. The performance of the model and its generalization ability are measured using key indicators such as R-squared (R^2), explained variance score (EVS), mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), maximum error, mean squared logarithmic error (MSLE), and mean absolute error (Med AE). During training, the model shows excellent performance. Both the R^2 and EVS values are 0.9986, indicating that the model can account for almost all of the variation in the training data. The error metrics are significantly low - MSE at 0.0011 and RMSE at 0.0328 - indicating highly accurate predictions. Additionally, the MAE of 0.0197 and the minimum maximum error of 0.0667 support the conclusion that the model fits the training data very well [27]. Furthermore, both MSLE and Med AE are essentially zero, highlighting the accuracy of the model during the learning phase.

Table 1. Descriptive Statistics.

	Joint Angle 1 (°)	Joint Angle 2 (°)	Motor Torque (Nm)	Sensor Delay (MS)	Battery Voltage (V)	End-Effector Error (mm)
Count	20.0000	20.0000	20.0000	20.0000	20.0000	20.0000
mean	58.2500	58.4500	1.5000	11.2000	23.7900	0.7795
std	22.4168	18.9667	0.3613	2.7644	0.9182	0.3902
min	20.0000	25.0000	1.0000	7.0000	22.3000	0.2800
25%	41.5000	47.2500	1.2000	9.0000	22.9500	0.4375
50%	59.0000	57.5000	1.4500	11.0000	23.9500	0.7650
75%	72.7500	70.5000	1.7250	13.2500	24.5250	0.9625
max	95.0000	90.0000	2.2000	16.0000	25.1000	1.5000

Table 2. AdaBoost Regression Models Battery Voltage (V) Train and Test performance metrics.

AdaBoost Regression	Train	Test
R2	0.9986	0.7666
EVS	0.9986	0.7790
MSE	0.0011	0.1995
RMSE	0.0328	0.4466
MAE	0.0197	0.3969
Max Error	0.0667	0.7000
MSLE	0.0000	0.0003
Med AE	0.0000	0.4375

Table 3. Random Forest Regression Models Battery Voltage (V) Train and Test performance metrics.

Random Forest Regression	Train	Test
R2	0.9742	0.8553
EVS	0.9755	0.8621
MSE	0.0192	0.1236
RMSE	0.1386	0.3516
MAE	0.1174	0.2955
Max Error	0.2570	0.5575
MSLE	0.0000	0.0002
Med AE	0.1078	0.3312

In contrast, the experimental results indicate a decrease in predictive accuracy. The R^2 score decreases to 0.7666 and the EVS to 0.7790, indicating that while the model retains a reasonable level of predictive power, it is significantly less accurate on unobserved data. The increase in MSE to 0.1995, RMSE to 0.4466, and MAE to 0.3969 reflects the increased prediction error during the experiment. The maximum observed error also increases significantly to 0.7000, indicating the presence of outliers or models that are difficult to predict [27]. Similarly, the mean absolute error increases to 0.4375, indicating less consistency in the experimental predictions.

Table 3 shows the performance evaluation of the random forest regression model for estimating the estimated battery voltage (V) on both the training and test datasets. A range of metrics are used to measure the model performance, including R-squared (R^2), explained variance score (EVS), mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), maximum error, mean squared logarithmic error (MSLE), and mean absolute error (Med AE) [28]. During training, the model shows strong predictive power, reaching 0.9742 R^2 and 0.9755 EVS. These scores indicate that the model accounts for almost 97% of the variance in the training data. Furthermore, the MSE of 0.0192 and RMSE of 0.1386 indicate a low level of prediction error. The MAE value of 0.1174 reflects small average deviations, while the maximum error of 0.2570 and the Med AE of 0.1078 confirm that extreme errors are rare in the training

phase. When evaluating the test data, the model continues to perform well with a slight decrease in accuracy. The R^2 score decreases to 0.8553 and the EVS to 0.8621, indicating that the model explains a significant portion of the variance in the data that is not yet observed. A slight increase in the MSE (0.1236) and RMSE (0.3516) indicates a moderate decline in prediction accuracy. The MAE increases to 0.2955, while the maximum error grows to 0.5575, indicating a wide spread in the error values. Similarly, the Med AE increases to 0.3312, reflecting less consistency among individual predictions [29]. Despite this, the MSLE remains very low at 0.0002, which shows the robustness of the model with respect to logarithmic error.

Table 4 describes the performance of the XG Boost regression model in predicting battery voltage (V) using the training and testing datasets. The evaluation is based on several standard regression performance indicators, including R-squared (R^2), explained variance score (EVS), mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), maximum error, mean squared logarithmic error (MSLE), and mean absolute error (Med AE). During the training phase, the model provides flawless prediction accuracy, with both R^2 and EVS achieving a perfect score of 1.0000. This indicates that the model accounts for all the variation in the training data. In support of this, the error metrics are exceptionally low: MSE is effectively zero, RMSE is just 0.0009, and MAE is 0.0007. Similarly, the maximum error of 0.0015 and the Med AE of 0.0005 highlight the very accurate fit of the model to the training data, confirming that it performs with almost perfect accuracy on known inputs.

Table 4. XG Boost Regression Models Battery Voltage (V) Train and Test performance metrics.

XG Boost Regression	Train	Test
R2	1.0000	0.6570
EVS	1.0000	0.6606
MSE	0.0000	0.2931
RMSE	0.0009	0.5414
MAE	0.0007	0.4955
Max Error	0.0015	0.7532
MSLE	0.0000	0.0005
Med AE	0.0005	0.5414

However, the performance of the model drops significantly when evaluated on the test dataset. The R^2 drops to 0.6570 and the EVS drops to 0.6606, indicating that the model only captures about 66% of the variance in the unseen data. The experimental error metrics rise significantly, with the MSE increasing to 0.2931, the RMSE increasing to 0.5414, and the MAE increasing to 0.4955. The maximum error also increases sharply to 0.7532 and the Med AE increasing to 0.5414, indicating less consistent prediction accuracy. Although the MSLE is low at 0.0005, this provides limited confidence given the wide performance degradation.

Table 5. Decision Tree Regression Models Battery Voltage (V) Train and Test performance metrics.

Decision Tree Regression	Train	Test
R2	1.0000	0.8040
EVS	1.0000	0.8157
MSE	0.0000	0.1675
RMSE	0.0000	0.4093
MAE	0.0000	0.3500
Max Error	0.0000	0.7000
MSLE	0.0000	0.0003
Med AE	0.0000	0.3000

Table 5 summarizes the performance of the decision tree regression model in predicting battery voltage (V) for the training and test datasets. The evaluation uses common regression metrics such as R-squared (R^2), explained variance score (EVS), mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), maximum error, mean squared logarithmic error (MSLE), and mean absolute error (Med AE). During the training phase, the model achieves correct results, with both R^2 and EVS equal to 1.0000, indicating that it fully explains the variance in the training data. All error metrics – MSE, RMSE, MAE, maximum error, MSLE, and Med AE – are zero, demonstrating that the model fits the training data perfectly without any prediction errors. While this level of accuracy indicates an excellent fit, it also raises concerns about overfitting, where the model may not generalize well to new data. When evaluated on the test dataset, the model performance decreases, but remains robust. The R^2 and EVS decrease to 0.8040 and 0.8157, respectively, showing that the model explains approximately 80% of the variance in the unobserved data. The error values increase, with MSE being 0.1675 and RMSE being 0.4093, indicating moderate deviations in the predictions. The MAE of 0.3500 and Med AE of 0.3000 indicate that, on average, the predicted values differ by about 0.3 to 0.35 volts from the actual battery voltages. The maximum error also increases to 0.7000, indicating occasional large prediction errors. However, the low MSLE of 0.0003 indicates that the model handles logarithmic differences effectively.

Figure 1 shows a detailed pairwise analysis matrix illustrating the relationships between six essential parameters of a robot system: joint angle 1, joint angle 2, motor torque, sensor delay, battery voltage, and end-effector error. The diagonal plots are histograms showing the distribution of each variable. Both joint angle 1 and motor torque show very normal distributions, whereas end-effector error is right-skewed, indicating that most error values are low with a few high outliers. The scatter plots below the diagonal highlight significant correlations between the parameters [29].

There is a strong linear relationship between motor torque and joint angle 1, indicating that these factors are mechanically coupled within the robot's design. In addition, end-effector error is positively correlated with motor torque, joint angle 1, and sensor delay, suggesting that increases in

these parameters will reduce position accuracy. Conversely, battery voltage shows a negative correlation with end-effector error, indicating that higher battery voltage is associated with improved accuracy. Joint angle 2 shows weak correlations with other variables, indicating that its state has limited influence on overall system behavior within the observed data range. Several scatter plots exhibit clear clustering patterns and strong linear trends, particularly those involving motor torque and joint angle 1, indicating reliable dependencies. These strong relationships indicate the potential for useful predictive modeling using these parameters, especially where tight linear relationships exist.

Figure 2 quantifies the linear relationships identified in the pairwise analysis by presenting the Pearson correlation coefficients in a color-coded heat map. Darker blue shades indicate stronger correlations, while lighter colors indicate weaker correlations. End-effector error shows very strong positive correlations with motor torque (0.97), joint angle 1 (0.93), and sensor delay (0.89), confirming these variables as important predictors of positioning accuracy. The heat map also highlights a strong negative correlation between battery voltage and end-effector error (-0.95), emphasizing the important role of power management in maintaining robot accuracy. This negative relationship indicates that fluctuations in battery voltage directly affect motor operation and control stability, with higher voltages supporting more reliable and accurate positioning.

In addition, the matrix exhibits significant multicollinearity among the predictor variables, especially between joint angle 1, motor torque, and sensor delay, where the correlation values range from 0.83 to 0.94. This indicates that these features are closely related to each other. In contrast, joint angle 2, which consistently shows weak correlations with other parameters, ranging from 0.18 to 0.30, supports the idea that this joint has minimal impact on the performance of the overall system. This indicates that the second joint acts somewhat independently or within a range that does not significantly affect the accuracy [30]. High correlations among key predictors indicate potential redundancy in the dataset, which may need to be considered during model building and feature selection to avoid overfitting or multicollinearity issues.

Figure 3 depicts the performance of the AdaBoost regression model in predicting battery voltage based on the training dataset. The scatter plot compares the predicted battery voltage values with the actual measurements, with a diagonal dashed line representing the correct predictions (predicted equals actual). The data points closely follow this best fit line, indicating that the AdaBoost model effectively captures the patterns in the training data with very low prediction errors. The points are tightly clustered on the diagonal across the voltage range, from about 22.5V to 25V, demonstrating consistent accuracy regardless of the specific voltage level [29]. This consistent performance indicates that the ensemble method, which combines multiple weak learners, produces a robust and reliable predictive model. Furthermore, the absence of significant outliers or systematic bias indicates that the model has learned the underlying

relationships well without overfitting the noise in the training data. Such robust performance during training indicates that it can accurately predict battery voltage using other system parameters. This predictive capability is valuable for enabling proactive battery management and system optimization [30]. By anticipating voltage changes before they impact system accuracy, this model can support predictive maintenance efforts and help maintain optimal robot performance over time.

Figure 4 illustrates the performance of the AdaBoost model when applied to the unseen test data, highlighting its

ability to generalize beyond the training set. Although the predicted values generally follow the diagonal reference line that represents correct predictions, there is a significantly higher scatter compared to the training results, which is common when moving from fit to prediction on new data. The points are mostly clustered near the ideal line, but show high variability, especially within the intermediate voltage values between 23 and 24 volts. The model maintains reasonable accuracy over most of the voltage spectrum, but some predictions show larger deviations from the true values than observed during training.

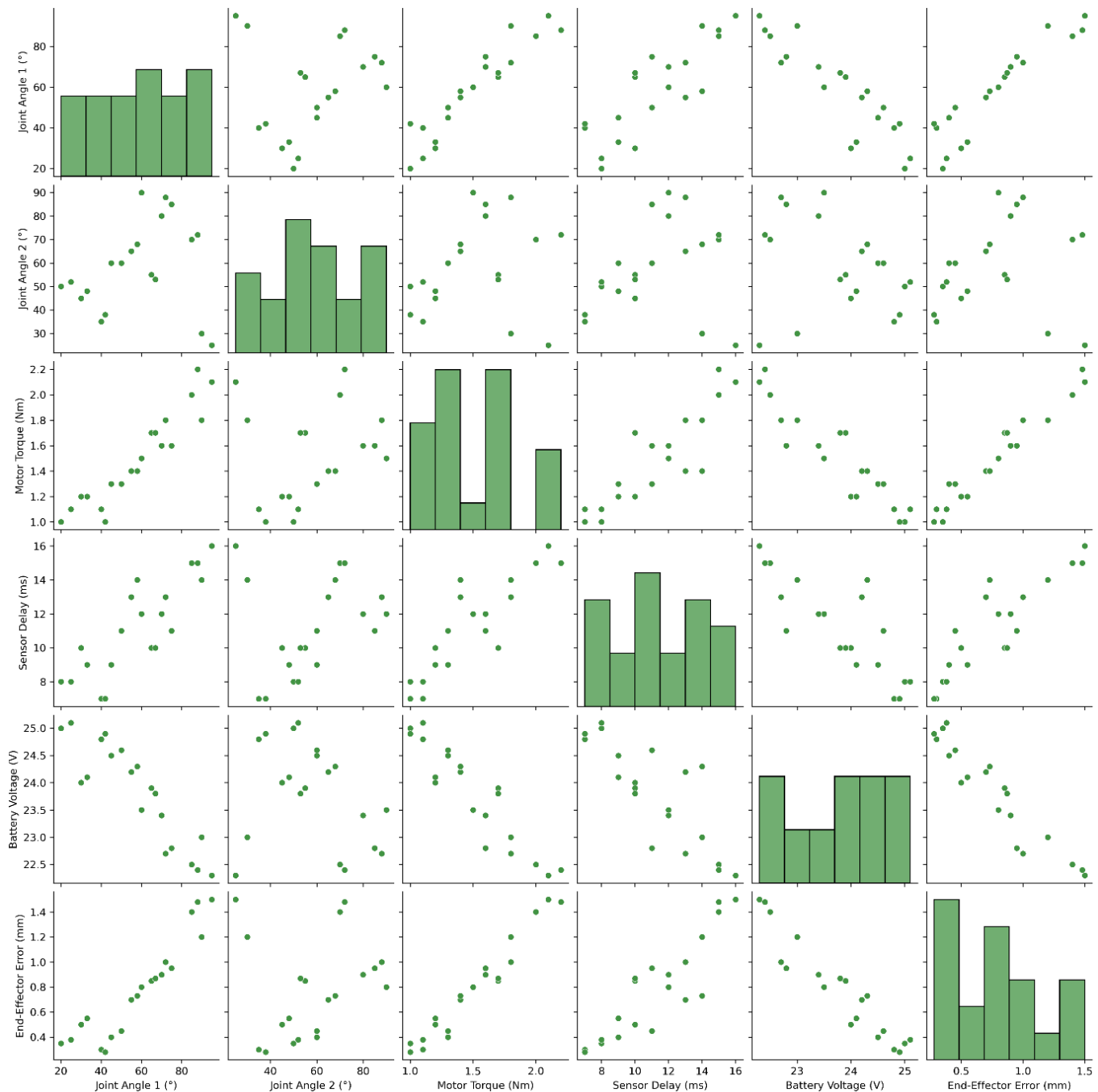


Fig. 1. Effect of Process Parameters.

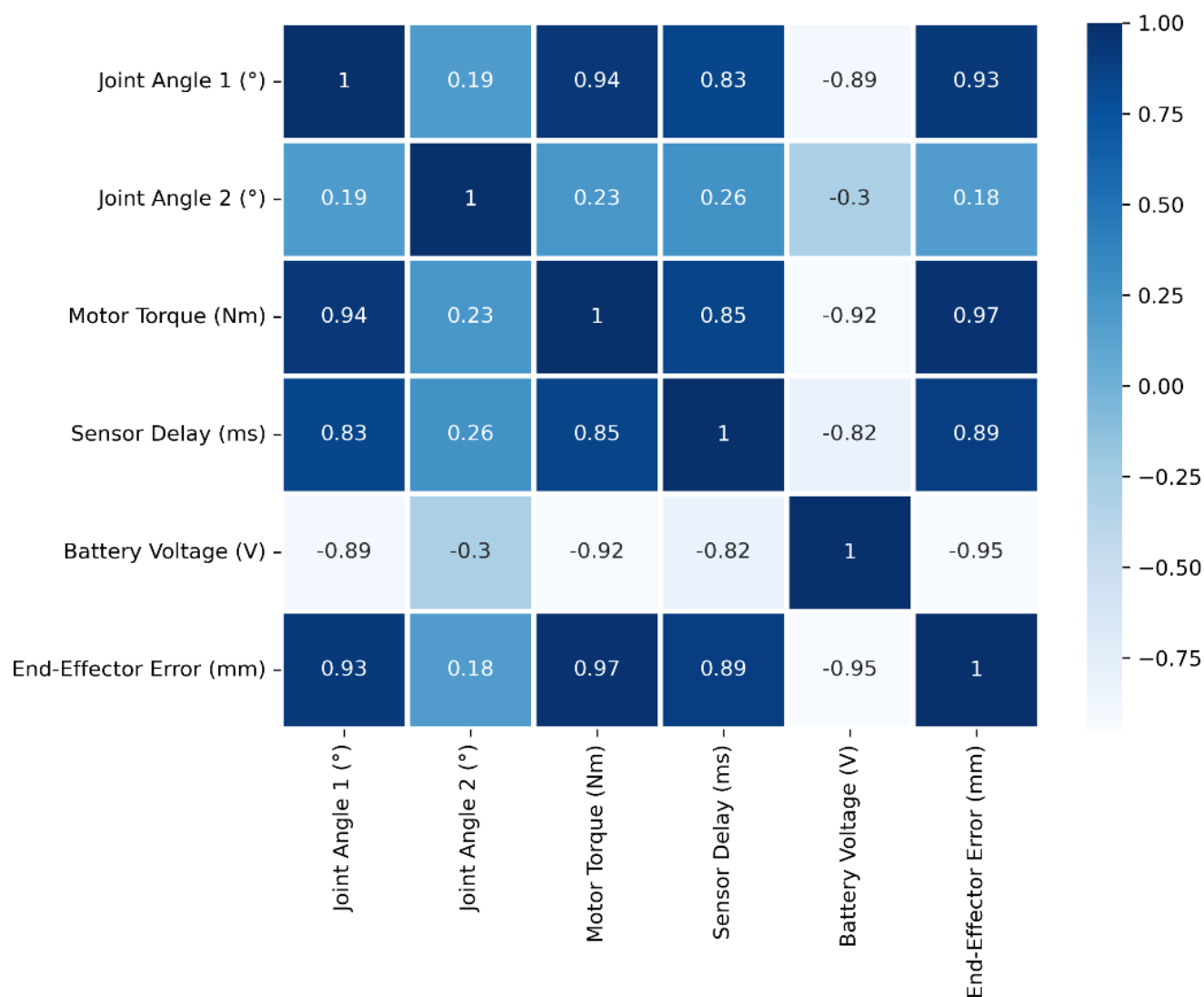


Fig. 2. Correlation heatmap.

Predicted vs Actual Battery Voltage (V)(Training data)

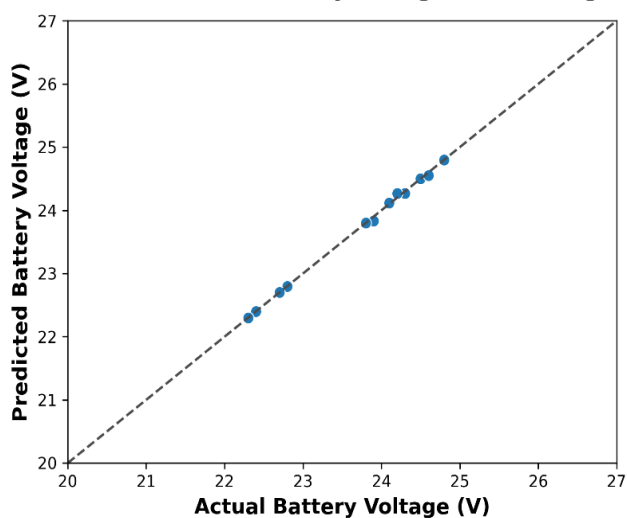


Fig. 3. AdaBoost Regression Battery Voltage (V) Training.

Predicted vs Actual Battery Voltage (V)(Testing data)

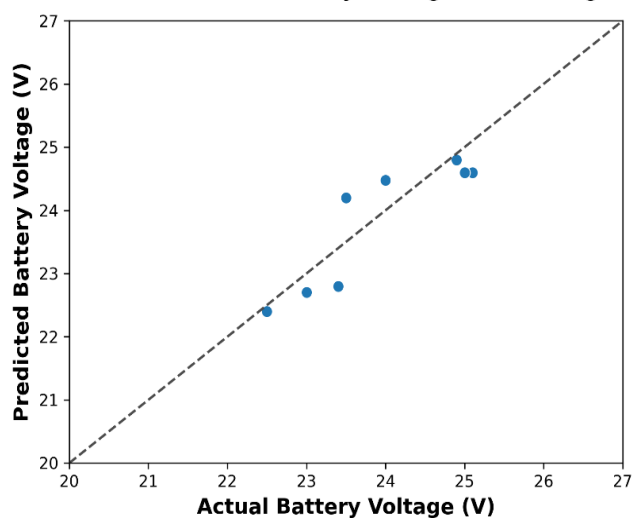


Fig. 4. AdaBoost Regression Battery Voltage (V) Testing.

This increase in variability indicates that the model faces challenges in fully capturing new data patterns, although its overall predictive performance is satisfactory for many practical purposes. Importantly, the scatter of points above and below the diagonal line indicates that there is no consistent overestimation or underestimation bias. These experimental results indicate that while AdaBoost provides useful voltage predictions, it may be somewhat over-fitted to the training data or may not be able to fully model the more complex relationships in the test set. This emphasizes the need for rigorous validation to properly assess the robustness and reliability of the model before it can be used in real-world applications [29].

Figure 5 illustrates the performance of the Random Forest regression model on the battery voltage prediction training dataset. The scatter plot shows excellent prediction accuracy, with data points clustering tightly along the diagonal reference line, indicating correct predictions. Compared to the AdaBoost model, the Random Forest shows a close fit with less deviation from the best predictions over the entire voltage range. The ensemble nature of the model is clearly effective in capturing complex, nonlinear relationships while maintaining stability across varying voltage levels [30]. The consistent accuracy from the low end (around 22V) to the high end (up to 25V) indicates that the Random Forest successfully handles the correlations between input features and battery voltage. The minimal spread of points around the diagonal demonstrates that bootstrap aggregation combined with random feature selection helps reduce variance without significantly increasing bias. This excellent training performance highlights the strength of Random Forest in handling multicollinearity and complex feature dependencies, often without the need for extensive hyperparameter tuning. Nevertheless, the nearly perfect training fit raises concerns about overfitting, which emphasizes the importance of evaluating the model's performance on test data to determine its generalization ability and real-world applicability [29].

Predicted vs Actual Battery Voltage (V)(Training data)

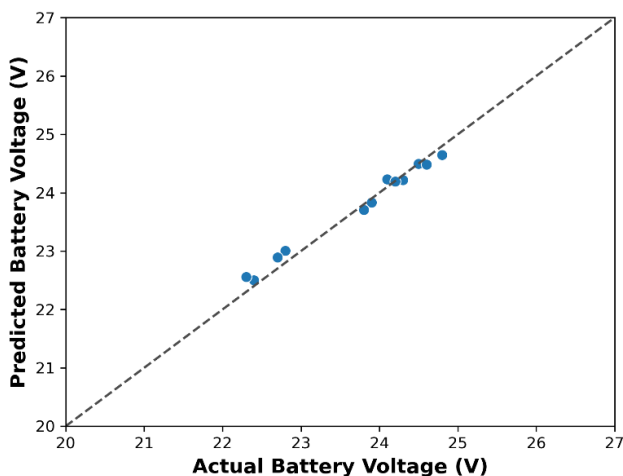


Fig. 5. Random Forest Regression Battery Voltage (V) Training.

Figure 6 depicts the performance of the random forest regression model on a test dataset for battery voltage prediction. The scatter plot compares the actual battery voltage values (x-axis) with the model's predicted values (y-axis). Most of the points closely follow the diagonal line, indicating nearly perfect predictions, indicating strong overall accuracy. However, some data points show small deviations from this ideal line, particularly within the mid-range voltage values, indicating small instances of over- or under-prediction. This spread indicates that, while the model generalizes well to unobserved data, it may struggle to capture subtle or less frequent variations present in the test set. The ensemble nature of a random forest helps to effectively model complex nonlinear relationships, but factors such as limited sample size or less representative data patterns can cause modest degradation in prediction accuracy in some cases.

Predicted vs Actual Battery Voltage (V)(Testing data)

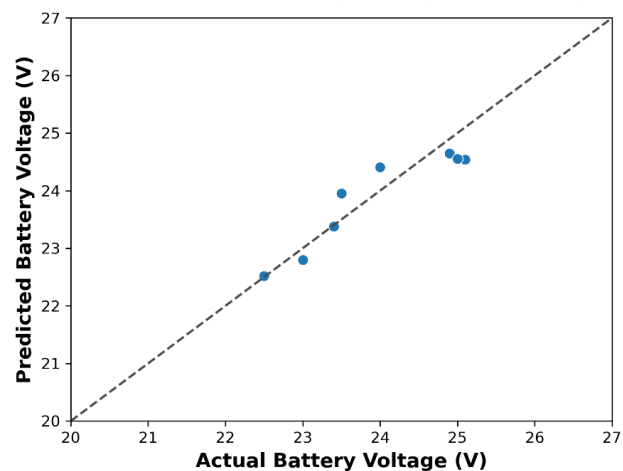


Fig. 6. Random Forest Regression Battery Voltage (V) Testing.

Figure 7 illustrates the training performance of the XG Boost regression model in predicting battery voltage. The data points are clustered very closely on the ideal diagonal line, showing a strong correspondence between the actual and predicted values. This highlights the impressive ability of the model to capture complex patterns and interactions within the training dataset. As a gradient-boosted tree method, XG Boost effectively reduces the training error through its iterative learning process combined with regularization techniques. However, the observed near-perfect fit may also suggest possible overfitting, where the model may have learned noise or specific anomalies of the training data. Despite this, the results confirm the high accuracy and robust learning ability of XG Boost on structured training data.

Figure 8 illustrates the predictive performance of the XG Boost model on the test dataset. While many predicted values fit well with the best diagonal line, indicating generally good accuracy, several significant deviations exhibit signs of

overfitting. In particular, predictions within the mid-range voltage values (22–24 V) show some cases of under- and overestimation, which may be due to the importance of training data patterns that do not fully generalize to the new data of the model. Nevertheless, the predictions are overall very well clustered, demonstrating that XG Boost maintains a strong ability to generalize. Although this model exhibits some tendency towards overfitting, it remains a reliable regression method when properly tuned, especially to capture the typical nonlinear behavior of battery voltage in robotic systems.

Predicted vs Actual Battery Voltage (V)(Training data)

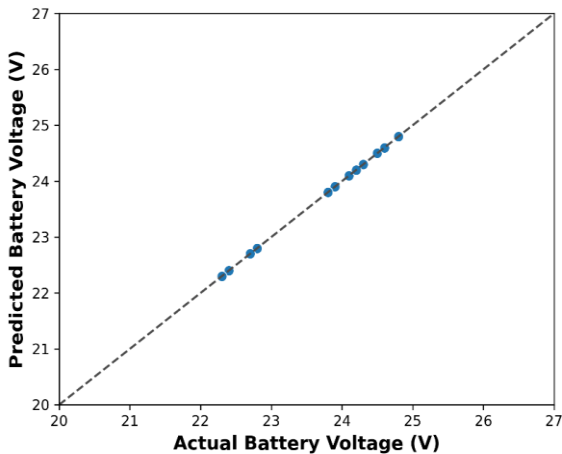


Fig. 7. XG Boost Regression Battery Voltage (V) Training.

Predicted vs Actual Battery Voltage (V)(Testing data)

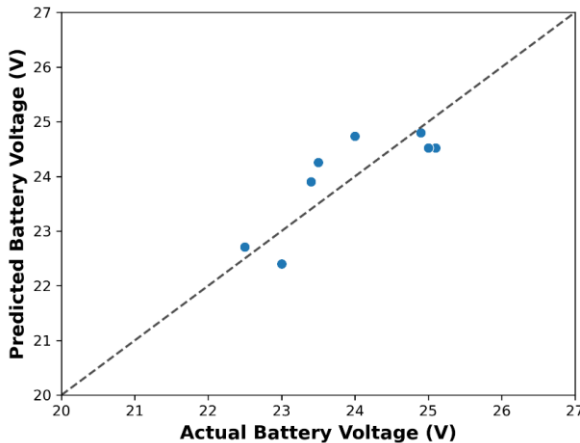


Fig. 8. XG Boost Regression Battery Voltage (V) Testing.

Figure 9 illustrates the performance of the decision tree regression model on the training dataset. The predicted values match the actual measurements almost perfectly, as evidenced by the tight clustering of data points on the diagonal line. This almost perfect fit demonstrates the model's strong ability to learn the training data. However, such flawless alignment is a classic symptom of overfitting,

a common problem with decision trees, where the model memorizes training examples instead of learning common patterns. This limits its ability to accurately predict new, unseen data. The training error, which is close to zero, underscores the importance of using ensemble methods such as random forest to reduce overfitting and improve model robustness.

Predicted vs Actual Battery Voltage (V)(Training data)

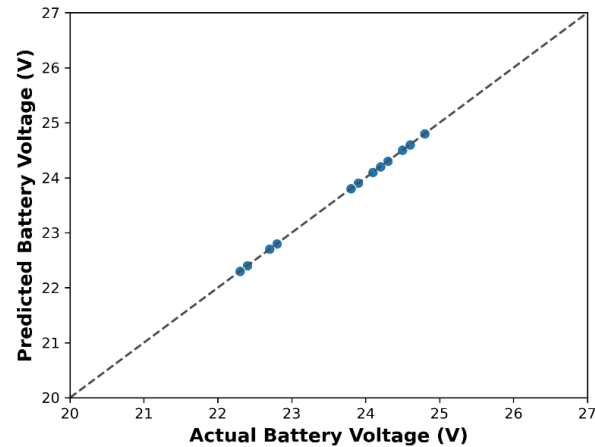


Fig. 9. Decision Tree Regression Battery Voltage (V) Training.

Predicted vs Actual Battery Voltage (V)(Testing data)

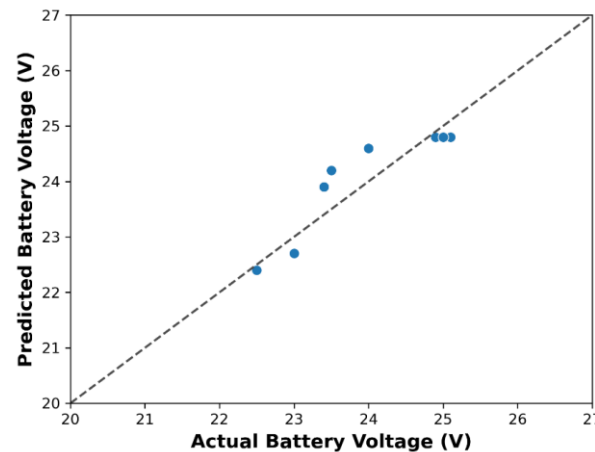


Fig. 10. Decision Tree Regression Battery Voltage (V) Testing.

In contrast to its nearly perfect training results, Figure 10 highlights the limitations of the decision tree model on the test data. The scatterplot shows considerable spread around the diagonal line, with many points showing significant deviation from the true values. This increased variability reflects a decline in prediction accuracy, confirming the overfitting observed during training. Although some predictions are close to the true values, the model struggles to generalize to new patterns that have not been observed

before. This discrepancy indicates that the model has learned noise rather than meaningful underlying relationships. Therefore, despite the simplicity and interpretability of decision trees, they require careful tuning or ensemble methods to improve their generalization performance on unseen data.

4. CONCLUSION

This in-depth study successfully applied machine learning regression methods to predictive modeling in robotic systems, with a particular focus on predicting battery voltage – a key parameter in ensuring optimal system performance. By comparing four regression algorithms – decision tree, random forest, Ada boost and XG boost – the research provided valuable insights into their strengths and limitations in the context of robotic operational data. The findings confirmed strong relationships between system variables and performance metrics, identifying battery voltage as a key indicator of robotic health and accuracy. The strong negative correlation between battery voltage and final-effect error (-0.95) highlights the critical role of power management in maintaining operational accuracy. This insight is directly relevant to improving predictive maintenance and enabling real-time monitoring of robotic systems. Among the models tested, Random Forest Regression stood out for its balance of accuracy and generalizability, as well as its solid training results ($R^2 = 0.9742$) and high predictive performance on the test data ($R^2 = 0.8553$). Its strength is largely due to the use of bootstrap aggregation and random feature selection in the ensemble technique, which helps mitigate overfitting in the data and capture complex, nonlinear relationships - making it more suitable for modeling robotic systems with interacting variables. In contrast, the Decision Tree and XG Boost models showed severe overfitting. While both achieved perfect or near-perfect accuracy on the training data, their test performance dropped significantly. Decision Tree regression training methods suffered from memorization without effective generalization, while XG Boost, despite achieving $R^2 = 1.0000$ in training, saw a significant decline in test accuracy ($R^2 = 0.6570$), underscoring the need for better regularization and adjustment in gradient boosting approaches. The results of this study go beyond theoretical research, with practical applications in predictive maintenance, autonomous systems, and performance optimization. Accurate battery voltage prediction based on real-time parameters allows for timely maintenance, reduces the risk of unexpected failures, and improves robot performance in industrial environments. Future work should aim to increase the dataset size for higher model reliability, explore deep learning techniques to capture more complex patterns, and develop architectures for real-time application. Additionally, integrating predictive models with adaptive control systems will pave the way for self-optimizing robots capable of maintaining peak performance throughout their service life.

DECLARATIONS

Ethical Approval

We affirm that this manuscript is an original work, has not been previously published, and is not currently under consideration for publication in any other journal or conference proceedings. All authors have reviewed and approved the manuscript, and the order of authorship has been mutually agreed upon.

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All of the data obtained or analyzed during this study is included in the report that was submitted.

Conflicts of Interest

The authors declare that they have no financial or personal interests that could have influenced the research and findings presented in this paper. The authors alone are responsible for the content and writing of this article.

Authors' contributions

All authors contributed equally in the preparation of this manuscript.

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