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Research Article

Prediction of Remaining Useful Life for Plastic Injection Molding Machines Using Artificial Intelligence Methods

Gözde ASLANTAS [1,*], Mustafa OZSARAC [1], Merve RUMELLI [1], Tuna ALAYGUT [1], Gözde BAKIRLI [1], Derya BIRANT [2]

[1] VESTEL Electronics, Turkey
[2] Dokuz Eylul University, Engineering Faculty, Department of Computer Engineering, Turkey

Abstract
Sustaining productivity with guaranteed machine availability is of the utmost significance while reducing costs. With the rising technology and the collected data in the industry, accomplishing such a goal is not fictional anymore. This paper proposes an artificial intelligence-based model that predicts the remaining useful life (RUL) of the plastic injection molding machines before requiring maintenance. Data collected from machines in production via sensors is preprocessed by performing various techniques, and anomalies in the data are detected and cleaned. Based on the historical data, the RUL of the machine, which is the duration until maintenance is required, is calculated, and the data is labeled with the RULs accordingly. In the proposed method, the labeling step is followed by feature engineering where the useful features are extracted from the raw data, such as entropy, peak to peak, and crest factor. A feature selection method is also applied to determine their contribution to the estimation accuracy of the RULs. As a comparison, we experimented with various regression models along with various evaluation metrics. The experimental results showed that our proposed approach achieved around 98% in the R^2 performance metric.
Keywords: Artificial intelligence; manufacturing; plastic injection molding machines; predictive maintenance; regression; remaining useful life.

1. Introduction

Any failures and outages of machines in industrial areas will result in a degradation in production, and hence significant costs and penalties in procurement. Maintenance is the key activity in manufacturing, in terms of its impact on cost reduction, and prolonging the life of equipment parts in a reliable way. The main goal of the maintenance activities is to maximize the durability of the machines while minimizing the cost of downtime in production, thus ensuring reliability and continuity in procurement.

Maintenance strategies can be divided into three categories [1] by common usage:

1. *Run-to-failure maintenance* (R2F): Run-to-failure maintenance, which is also called reactive or corrective maintenance, is the simplest approach as it aims to repair the machine or the system after the failure occurred.
2. *Preventive maintenance* (PvM): Preventive maintenance is employed on a scheduled basis in order to prevent any failures without taking into account the health statuses of the machines. This regular maintenance usually prevents failures before it occurs as it aims to but causes additional cost when it is performed unnecessarily.
3. *Predictive maintenance* (PdM): Predictive maintenance is performed as a result of a prediction mechanism based on the historical maintenance data or health states in order to act prior to any failures in the system.

Based on the requirements, each of these maintenance types have different benefits and disadvantages. Negligence of any type of maintenance may result in costly failures, performance issues, and thus production impediments. The frequency and timing of the maintenance are substantial though. Regardless of the health status of the machines, repetitive and non-optimized maintenance can increase the cost as the remaining useful life (RUL) of the machine is not being used effectively. Postponing the maintenance till the time for a machine approaches to zero may also lead to unexpected consequences which will be more costly. Based on the foreseen impacts, utilization of RUL is the most highlighted objective in order to perform sustainable maintenance with long-running equipment.

With the recent advancements in artificial intelligence, big data techniques, and the internet of things (IoT), predictive maintenance (PdM) has become an indispensable part of the new industrial era. PdM involves sensor data monitoring, data-driven condition review, fault diagnosis, fault alerts, and so on. As a benefit of PdM, in comparison with other strategies, the state of the system is observed and evaluated in real-time based on certain parameters of the system. Hence, a system-specific determination is done.

*Corresponding author e-mail address: gozde.aslantas@vestel.com.tr

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In this study, predictive maintenance is exploited to determine the RULs of the plastic injection molding machines. Plastic injection molding is a sequential process where plastic is melted, pressed into the mold, cooled to solidify, and removed from the mold as a three-dimensional shape. This process is applied in industrial areas using plastic injection molding machines in two stages: Injection, and Clamping. As a final product, the plastic injection molding machines produce various components such as TV components (i.e., TV cabinets, and stand bases), and plastic components of mobile phones.

In this study, an artificial intelligence-based model is designed and developed by applying machine learning methods to provide the following important benefits:

- To decrease plastic injection molding machine downtime
- To reduce the number of major repairs
- To better management of plastic injection molding machines
- To reduce maintenance costs and operational risk, and so, save money
- To improve safety
- To increase efficiency
- To discover knowledge related to various plastic injection molding machine downtime problems

The main contributions of this paper can be summarized as follows. (i) It proposes an artificial intelligence-based model that accurately predicts the remaining useful life for plastic injection molding machines in the manufacturing industry. (ii) It compares different regression algorithms to determine the best one for predictive maintenance: random forest regression, decision tree regression, and extreme grading boosting regression. (iii) Our study is original in that it extracts useful features (i.e., entropy, peak to peak, and crest factor) from raw data by aggregating samples within a certain time period.

The paper is organized as follows. Section 2 gives a review of related work in the literature. Section 3 explains the proposed approach and the materials used in the study. Section 4 covers the description of the dataset and the experimental details along with the results. Section 5 presents the conclusion and our final thoughts about future work.

2. Literature Review

Remaining useful life (RUL) is the time between a machine’s current working state and its failure. RUL prediction is the attempt to estimate the remaining period of normal operation at a particular level of performance for an electronic machine or motor. RUL prediction helps managers to assess the health of machines and to make a maintenance schedule. RUL prediction has been studied in many different areas such as manufacturing [2], energy [3], automotive [4], industry [5], aviation [6], and marine [7].

Selecting the most appropriate machine learning (ML) algorithm is a big challenge for the RUL prediction. Table 1 presents the previous work related to the RUL prediction. In the literature, various ML methods have been explored in the field of predictive maintenance such as Extreme Learning Machine (ELM) [3], Relevance Vector Machine (RVM) [3], Linear Regression (LR) [8], Support Vector Machine (SVM) [9], Multi-Layer Perceptron (MLP) [10, 11], Particle Swarm Optimization (PSO) [12], Decision Tree (DT) [13], and K-Nearest Neighbors (KNN) [14]. Furthermore, ensemble learning methods have been used for RUL prediction such as Random Forest (RF) [8], Gradient Boosting (GBoost), and Extreme Gradient Boosting (XGBoost) [5, 15]. Hence, both bagging and boosting approaches have been tested for predictive maintenance. Moreover, deep learning methods have been applied successfully for the prediction of RUL such as Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN) [16], and Deep Neural Network (DNN) [13].

Some previous studies [11, 15] focused on classification tasks to estimate whether a machine will fail within a certain period of time. On the other hand, most previous works [2-4, 6, 7, 9, 10, 12, 16] performed a regression task to predict the RUL of equipment as a numerical value. Besides, several studies [8, 13, 14] have addressed both classification and regression tasks to solve the RUL prediction problem.

To evaluate the performance of the classification models, they used Accuracy (ACC), Precision (P), Recall (R), F1-Score (F), and Area Under Curve (AUC) metrics. On the other hand, the error evaluation of regression models was analyzed based on the Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and Coefficient of Determination (R^2).

Our work differs from the aforementioned studies in several aspects. First, we investigated the use of different regression algorithms to predict the RUL of plastic injection molding machines. Second, in the data preprocessing step, we extracted useful features (i.e., entropy, peak to peak, and crest factor) from raw data by aggregating samples within a certain time period.

Table 1. *Related studies (C: Classification R: Regression)*

Reference	Year	ML Algorithms	Task		Application	Evaluation	Sector
			C	R			
Zhao and Liu [2]	2022	CNN		√	Estimating RUL for bearings under different conditions and platforms	RMSE	Manufacturing
Yao et al. [3]	2022	PSO-ELM-RVM		√	Predicting RUL for lithium-ion batteries	RMSE, MAPE	Energy
Chen et al. [4]	2022	SVM		√	Prediction of RUL for fuel cell electric vehicle	MSE, MAPE	Automotive
Böttjer et al. [5]	2022	XGBoost	√		Predicting of RUL for moulds	ACC	Industry
Peng et al. [6]	2021	LSTM, CNN, RF, SVM		√	Predicting RUL for turbofan engine	RMSE	Aviation
Folcaner et al. [7]	2021	SVM, MLP, RF		√	Predicting RUL for fibre ropes	RMSE, R^2	Marine
Wu et al. [8]	2021	CNN, LSTM, LR, SVM	√	√	Prediction for tool wear in shaft production line	ACC, RMSE	Manufacturing
Ragap et al. [9]	2021	SVM, RF, GBoost, CNN, LSTM		√	Prediction of RUL of industrial equipment	RMSE	Industry
Kang et al. [10]	2021	MLP		√	Prediction of the failure of equipment in production lines	MSE	Manufacturing
Orru et al. [11]	2020	MLP, SVM	√		Fault prediction of a centrifugal pump (1: RUL<168, 0: otherwise)	ACC, P, R, F, AUC	Oil and Gas Industry
Bala et al. [12]	2020	RNN, LSTM, PSO		√	Predicting faults in airplane engines	MSE	Aviation
Utah and Jung [13]	2020	SVM, KNN, DT, RF, DNN	√	√	Fault state detection and RUL prediction in alternating solenoid-operated valves	ACC, P, R, F, MAE, MSE, RMSE	Nuclear Eng.
Trinh and Kwon [14]	2020	MLP, KNN, SVM, RF	√	√	Fault-type classification and RUL prediction	MSE, F	Manufacturing
Calabrese et al. [15]	2020	GBoost, RF, XGBoost	√		Prediction of RUL of woodworking machines (30, 20, 10-day RUL)	ACC, P, R, AUC	Industry
Zhang et al. [16]	2020	CNN, SVM, MLP, RNN, LSTM		√	Prediction of RUL of rotatory machine	MAE, RMSE	Manufacturing

3. Material and Methods

The remaining useful life is the time interval in which a machine, component, or motor can be used before it should be repaired or replaced. RUL prediction is useful to determine the machine or component maintenance time reasonably, reduce the accident probability, and improve manufacturing efficiency. RUL prediction is a challenging task due to the lack of an accurate predictive maintenance model.

In this study, we approached the RUL prediction of plastic injection molding machines as a regression problem. Figure 1 shows the general structure of the proposed approach. In the first step, sensor values and the maintenance date of the machines are collected, transferred, and stored in a cloud platform. In the data preparation step, raw data is transformed into a format where the sensor names and the timestamp that indicates the maintenance time are columns and renamed to parameters for machines. RUL for each timestamp when a collection of sensor values is calculated based on the maintenance/failure date. Missing values are eliminated and outliers are detected. Feature selection is performed based on the contribution of the features to the regression problem using several techniques, including random forest regression, permutation, and SHapley Additive exPlanations (SHAP). In addition, data is hourly aggregated using statistical methods such as min, max, mean, standard deviance, skewness, kurtosis, peak to peak, velocity, and entropy. In the training step, the most commonly-used regression methods are applied for benchmarking. As the main performance metric, the coefficient of determination (R^2) metric is used to measure how well the applied method fits the data. RUL prediction is performed by using the model for a new observation. In the next stage, the prediction results are presented to the user via an application for giving feedback about the RUL of the machine. Finally, the output of the model is taken into consideration by a manager for decision-making. Hence, an artificial intelligence-based model is designed and developed by applying machine learning methods to provide significant benefits such as reducing machine downtime, decreasing repair costs, improving efficiency, and increasing safety.

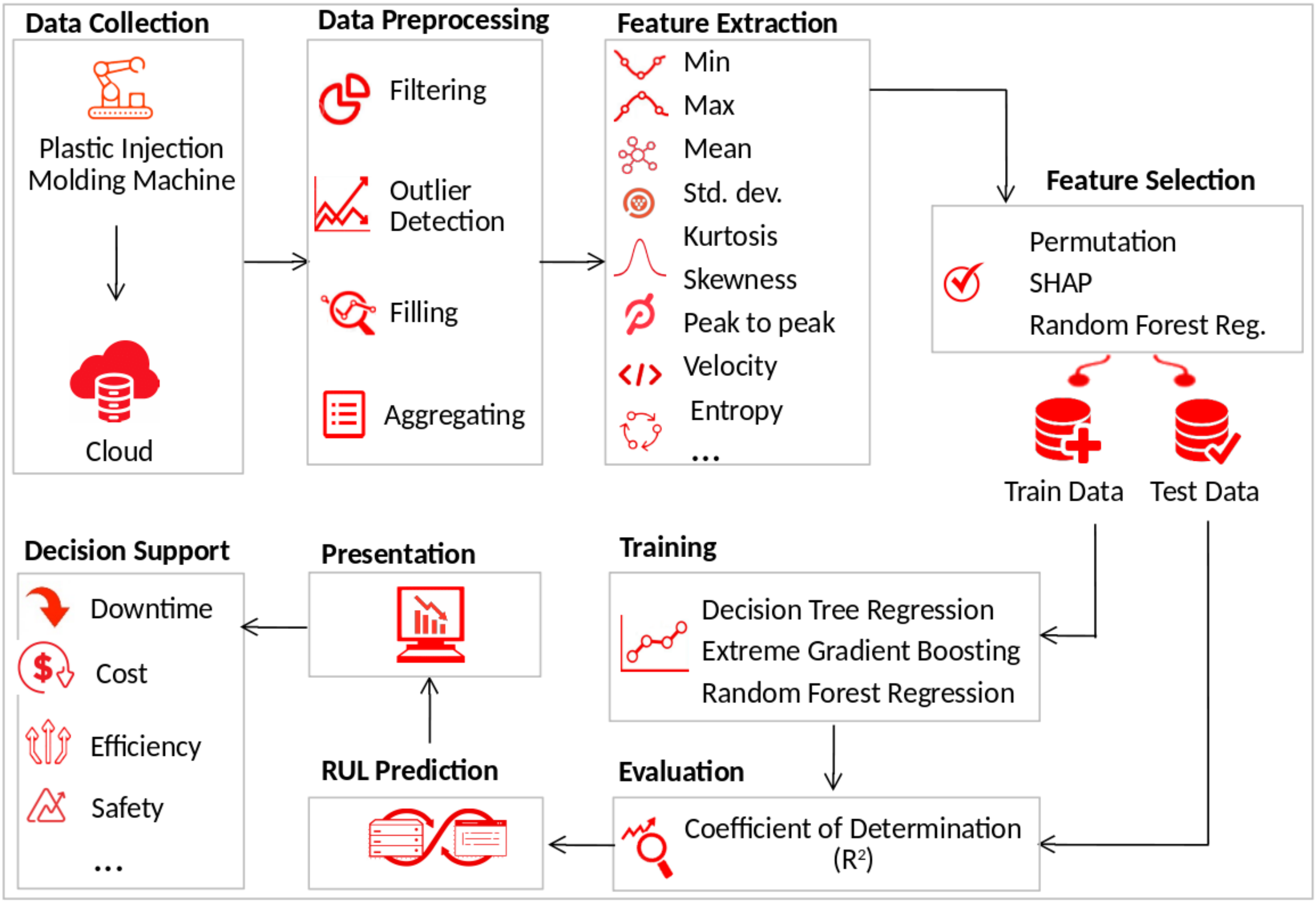

Figure 1. *The general structure of the proposed approach.*

In this study, the most common regression algorithms were used to construct a machine learning model for predictive maintenance: decision tree regression, extreme gradient boosting, and random forest regression. The description of these algorithms is given in Sections 3.1, 3.2, and 3.3, respectively.

3.1. Decision tree regression

The decision tree is one of the most commonly-used supervised learning algorithms utilized in both classification and regression problems. In this method, the inputs are split into nodes, and each node is branched into internal nodes until the leaf nodes. Thus, the input space is divided into non-overlapping nodes where each leaf node maps the input space to the corresponding target. In classification problems, the target variables belong to a discrete set of values while, in regression, they can take real numbers. In this study, a decision tree is applied to build a regression tree.

3.2. Extreme gradient boosting

Extreme gradient boosting (XGBoost) is an ensemble learning algorithm that is based on boosting the various number of decision trees by using gradient descent to optimize them when new decision trees are added to train and combining the estimates with the majority voting for classification or weighted sum for regression problems. It is a popular algorithm since it can handle different machine learning challenges. Its high performance in predictive maintenance has been reported in the literature [15].

3.3. Random forest regression

Random forest is an ensemble learning algorithm that constructs various numbers of decision trees, and the final estimator is chosen based on majority voting or averaging for classification and regression problems. The splits in the decision trees are performed based on the selected hyperparameters. Actually, random forest is typical bagging (bootstrap aggregating) method that utilizes a decision tree as the base learner. It is forced to consider only a subset *m* of samples and *n* of features randomly chosen. In this study, a random forest regressor was used for RUL prediction.

4. Experimental Studies

In this study, experimental evaluations of the machine learning methods were performed using real data obtained from plastic injection molding machines. In experimental settings, the grid search method was used for hyperparameter optimization. To validate models, 5-fold cross validation was used. As evaluation criteria, coefficient of determination (R^2) and mean absolute error (MAE) were used. The coefficient of determination or R^2 is the proportion of the total sum of squares between actual values and predicted values, as given in Eq. (1). Based on this evaluation metric, the best model was selected and used for the prediction. MAE depends on the mean of difference among predictions and real values, as given in Eq. (2). A larger R^2 indicates a better model, while a smaller MAE indicates a better prediction performance.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - P_i)^2} \tag{1}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} P_i - O_i \tag{2}$$

where n is the number of samples, P_i is the predicted value, and O_i is the observed value.

4.1. Dataset description and data preparation

Data was collected from a Turkish home and professional appliances manufacturing factory specialized in electronics. The dataset consists of machine name, sensor values, date of collection of sensor data, and maintenance date of three pilot plastic injection molding machines, namely HEP3204, HEP3207, and HEP3213. The size and general information of the raw data with the description of the sensors are presented in Table 2 and Table 3, respectively.

Table 2. *Size and time interval of the raw data.*

Machine Name	Time Interval	Data Size
HEP3204	September 2019 – September 2021	251K
HEP3207	June 2019 – September 2021	205K
HEP3213	May 2018 – September 2021	913K

Table 3. *Description of the sensor data.*

Sensor Name	Description
CLAMPING_FORCE_ACT	Clamping force peak value
CLAMPING_FORCE_SET	Clamping force set value
Closing force-Skx-actual value	Closing force-Skx-actual value
Cycle time-ZUx-actual value	Cycle time-ZU-sets value
HOLD_PRESS_STEP_1-10	Hold pressures between 1st and 10th steps
HYDR_HOLD_PRESS	Hydr. holding pressure peak value
Injection time-ZSx-actual value	Injection time
Material cushion smallest value-CPx-actual value	Material cushion smallest value
OIL_TEMPERATURE	Oil temperature

A pipeline of data preprocessing steps was applied to the raw data. First, the raw data was transformed into a flat table with sensor values, collection date, and maintenance date in columns. The presence of missing values could lead to erroneous results in data analysis and therefore possible errors in solving the regression problem. In order to handle missing or null values in the sensor data, each data attribute that has null values for less than 40% was filled with the result of linear interpolation of the not-missing values at start and end. Data attributes with high missing rates (>40%) and data rows with missing collection date as well were eliminated. After that, RUL was calculated by subtracting the collection date from the maintenance date. Thus, for a set of sensor values collected at a given time period, we added a new numeric column, the RUL value indicating the remaining maintenance time in days. We then removed the sensor collection date and maintenance date from the data as they are used for specifying the RUL value for training data.

Anomalies in data are one of the most significant factors which affect the estimations by causing overfitting or underfitting. Thus, detection of anomalies and dealing with them are essential steps in data preparation. In our study, we detected anomalies based on the z-score limit which was chosen empirically. Z score gives the standard deviations of the data points that are away from the mean which indicates that these data points are outliers. Thus, data with a standard deviation smaller than the specified z-score limit are detected as outliers. We investigated the impact of anomaly detection by performing an ablation study comparing the performance of the proposed approach with two settings: dropping anomalies or keeping them. As seen in Table 4, dropping anomalies from data increases the model performance. While the mean squared error was 10.92 without anomaly detection, it became 2.683 with anomaly detection using z-score. Similarly, the mean absolute error decreased from 1.015 to 0.288 for a plastic injection molding machine when anomaly detection was performed.

Table 4. *Comparative study for anomaly detection*

Score Metric	**Without Anomaly Detection**	**With Anomaly Detection using z-score (z-score limit =4)**
Mean Squared Error	10.92	2.683
Mean Absolute Error	1.015	0.288
R^2	0.994	0.998

Data aggregation is an essential part of data analysis that is performed to extract useful features from data and hence, provides a different perspective by enhancing the value of the information. Data rows were aggregated as 1-hour intervals and useful features were extracted for each interval by using statistical techniques, including min, max, standard deviance, mean, absolute mean, median, skewness, kurtosis, entropy, root mean square, peak to peak, crest factor, clearance factor, shape factor, and impulse.

We performed feature selection to emphasize the features that contribute to the regression problem the most, and thus determine the features that will be used in model construction. Feature Importance analysis was performed with the following feature importance techniques:

- *Permutation*: Evaluate the importance of the features when the randomly selected feature is shuffled while others are kept constant by measuring the decrease in the performance of the estimator. The higher value indicates the higher feature importance.
- *SHapley Additive exPlanations (SHAP)*: Evaluate the importance of the features when the randomly selected feature is shuffled while others are kept constant by measuring the contribution magnitude of the features.
- *Random forest feature importance*: Features are evaluated based on the decrease in node impurity where each feature is represented as a node, and the impurity is calculated by taking the probability of the samples that reach the node.

Features in the intersection set of the resulting applications were selected while other features were dropped.

4.2. Experimental results

In this study, various machine learning methods were applied to preprocessed data, and the results were evaluated in terms of R^2 and MAE for comparison. In Table 5, the performance results for each plastic injection molding machine are presented separately. According to the results, it is possible to say that the algorithms had no difficulty in predicting RUL values successfully. Hence, models constructed by tree-based algorithms are prominent models, especially for such regression problems. For example, the random forest algorithm achieved around 99% in the R^2 performance metric for the HEP3204 machine. The comparison in this table depicts that the random forest algorithm outperformed other methods for the HEP3207 machine, achieving the smallest MAE value (0.4615). The MAE results indicate that the proposed models can be successfully used to estimate the remaining useful life of the plastic injection molding machines with low error values.

Table 5. *Performance comparison.*

Algorithms	**Coefficient of Determination (R^2)**			**Mean Absolute Error (MAE)**		
	HEP3204	**HEP3207**	**HEP3213**	**HEP3204**	**HEP3207**	**HEP3213**
Decision Tree Regression	0.9979	0.9115	0.9860	0.6215	0.6659	1.7586
Extreme Gradient Boosting	0.9978	0.9189	0.9850	0.7033	1.0495	2.5900
Random Forest Regression	0.9948	0.9966	0.9745	1.0157	0.4615	3.4281

Figure 2 shows the average performance comparison of algorithms in terms of R^2. According to the results, the random forest regression algorithm is seen to have better performance than others on average. While RF regressor achieved 0.989 according to the performance metric, XGBoost and DT obtained the values of 0.967 and 0.965, respectively.

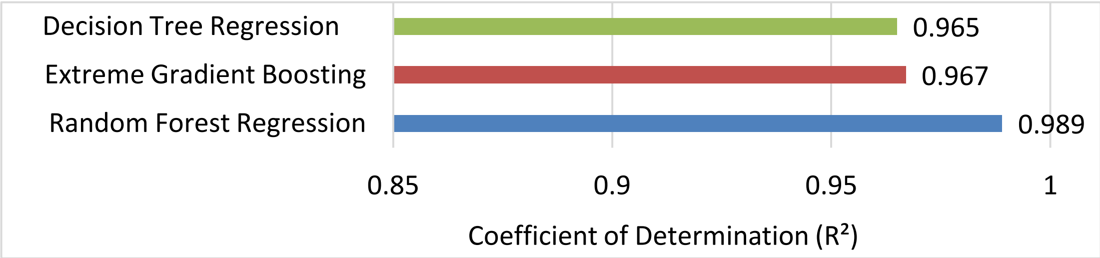

Figure 2. *Comparison of algorithms.*

Figure 3 presents the relation between actual and predicted RUL values for the plastic injection molding machine coded as HEP3204. It shows the effectiveness of the random forest model as an ensemble learning algorithm. Therefore, this model can be successfully used to predict the remaining useful life of the plastic injection molding machine in the future.

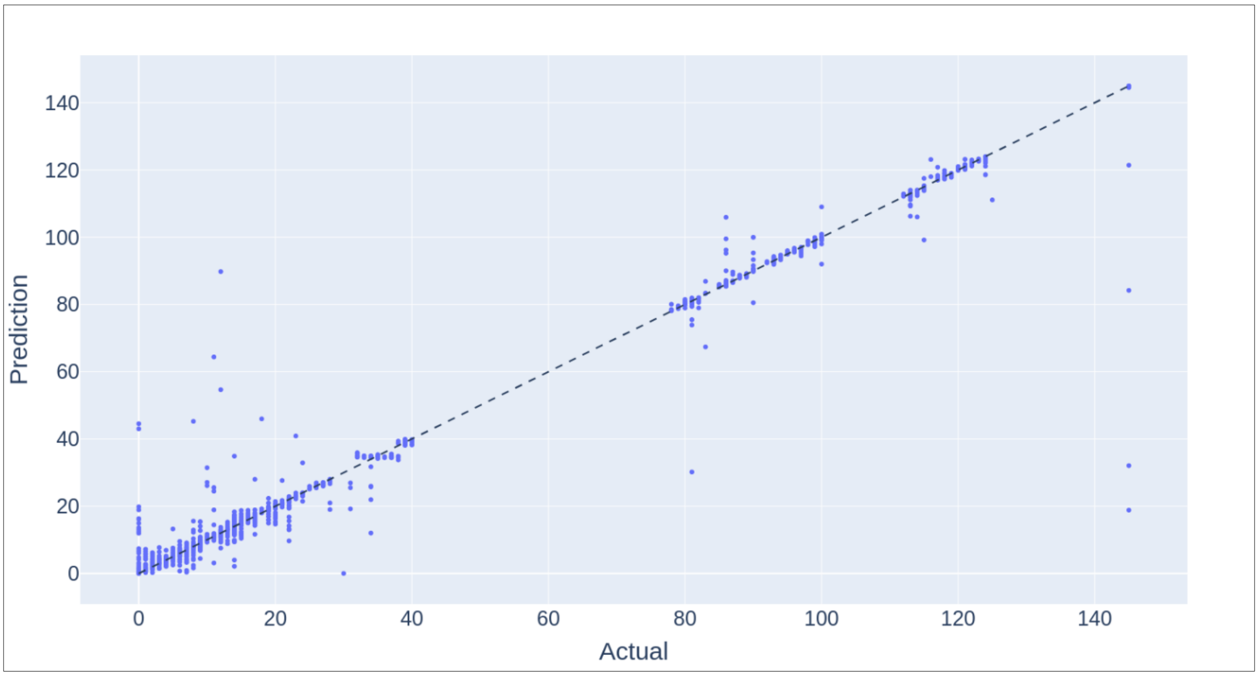

Figure 3. *Actual vs predicted RUL values.*

5. Conclusion and Future Work

In this study, we performed regression analysis for plastic injection molding machines based on the sensor values. Our goal was to estimate the remaining useful life of the machines with high accuracy. A pipeline of several data processing techniques was performed before machine learning algorithms were applied. We studied with the most prevalent regression algorithms, and based on the performance metrics, the Random Forest Regressor was the best model, achieving 0.989 in terms of R2, while XGBoost and Decision Tree Regression scored 0.967 and 0.965, respectively.

The findings of this study guided us to make a comprehensive analysis of the sensor data in terms of having a better insight into the contributions of each sensor to maintenance. In future work, we are planning to estimate the failure types of the machines based on the information we obtained from this research.

Declaration of Interest

The authors declare that there is no conflict of interest.

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