A comparative study of machine learning regression models for production systems condition monitoring

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ABSTRACT

This research investigates the benefits of different Machine Learning (ML) approaches in production systems, with respect to the given use case of considering the forming process and different friction conditions on hydraulic press response in between the phases of the sheet metal bending cycle, i.e. bending, levelling and movement. A framework for enhancing production systems with ML facilitates the transition to smarter processes and enables fast, accurate predictions integrated into decision-making and adaptive control. Comparative ML analysis provides insights into predictive regression models for hydraulic press condition recognition, enhancing process improvement. Our results are supported by performance evaluation metrics of predictive accuracy RMSE, MAE, MSE and R^2 for Linear Regression (LR), Decision Trees (DT), Support Vector Machine (SVM), Gaussian Process Regression (GPR) and Neural Network (NN) models. Given the remarkable predictive accuracy of the regression models with R^2 values between 0.9483 and 0.9995, it is noteworthy that less complex models exhibit significantly shorter training times, up to 437 times shorter than more complex models. In addition, simpler models have up to 36 times better prediction rates, compared to more complex models. The fundamentals illustrate the trade-offs between model complexity, accuracy and computational training and prediction rate.

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