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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.

ARTICLEINFO

Keywords:
Hydraulic press;
Metal forming;
Machine Learning (ML);
Linear Regression (LR);
Decision Trees (DT);
Support Vector Machine (SVM);
Gaussian Process Regression (GPR);
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Primerjalna študija regresijskih modelov strojnega učenja za spremljanje stanja proizvodnih sistemov

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POVZETEK

Ta raziskava preučuje prednosti različnih pristopov uporabe strojnega učenja (SU) v proizvodnih sistemih z vidika postopka preoblikovanja primera, ki upošteva različne pogoje trenja na odziv hidravlične stiskalnice med fazami cikla preoblikovanja pločevine, tj. preoblikovanjem, ravnanjem in premikanjem pločevine. Okvir za izboljšanje proizvodnih sistemov z uporabo SU omogoča lažji prehod na pametnejše procese ter hitre in natančne napovedi, vključene v odločanje in prilagodljivo krmiljenje. Primerjalna analiza SU nudi vpogled v napovedne regresijske modele za prepoznavanje stanja hidravlične stiskalnice, kar pripomore k izboljšanju procesa. Naši rezultati so podprti z metrikami vrednotenja uspešnosti napovedne natančnosti RMSE, MAE, MSE in R^2 za modele linearne regresije (LR), odločitvenega drevesa (DT), podpornih vektorjev (SVM), regresije Gaussovega procesa (GPR) in nevronskih mrež (NN). Glede na izjemno natančnost napovedovanja regresijskih modelov z vrednostmi R^2 med 0,9483 in 0,9995 je treba omeniti, da preprostejši modeli izkazujejo bistveno krajši čas učenja, ki je do 437-krat krajši od bolj zapletenih modelov. Poleg tega imajo preprostejši modeli do 36-krat boljšo stopnjo napovedi v primerjavi z bolj zapletenimi modeli. S temeljnimi podatki so ponazorjeni kompromisi med zapletenostjo modela, natančnostjo in računalniškim usposabljanjem ter hitrostjo napovedovanja.

PODATKI O ČLANKU

Ključne besede:
Hidravlična stiskalnica;
Preoblikovanje kovin;
Strojno učenje (ML);
Linearna regresija (LR);
Odločitveno drevo (DT);
Metoda podpornih vektorjev (SVM);
Regresija Gaussovega procesa (GPR);
Umetne nevronske mreže (ANN)

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