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Optimization of reliability and speed of the end-of-line quality inspection of electric motors using machine learning

Mlinarič, J.[a,b,*], **Pregelj, B.**[a], **Boškoski, P.**[a], **Dolanc, G.**[a], **Petrovčič, J.**[a]

[a]Jozef Stefan Institute, Jamova cesta 39, 1000 Ljubljana, Slovenia
[b]Jozef Stefan International Postgraduate School, Ljubljana, Slovenia

A B S T R A C T

Consistently maintaining high-end product quality in the production process is challenging. End-quality inspection must be highly sensitive to detect even minimal deviations, while being fast and accurate. However, quality inspection systems often face calibration intricacies, are time-consuming, and rely heavily on expert knowledge. They handle substantial data flows and inspect numerous features, some of which contribute minimally to the final grade. To address these challenges, the paper proposes employing statistically supervised machine learning methods for classification. Decision trees, Random forests, Bagging, and Gradient boosting classifiers are recommended for feature selection and accurate diagnosis, particularly for electric motor classification. By utilizing the feature importance attribute for feature selection, the proposed approach compares model accuracies, reducing ramp-up and commission times significantly. The study found that all suggested classifiers achieved high accuracy in classifying electric motors in end-of-line quality inspection system. Moreover, they effectively reduced the number of features and optimize database operations. Utilizing a reduced feature set streamlined diagnostic algorithms, accelerated learning, and improved model interpretability, enhancing overall efficiency and comprehension. Furthermore, analysing the feature importance attribute could simplify diagnostic hardware and expedite quality inspection by eliminating unnecessary steps. Newly generated models can also verify expert decisions on feature selection and limit adjustments, enhancing efficiency in production processes.

A R T I C L E I N F O

Keywords:
Quality inspection;
Fault detection;
Machine learning;
Feature selection and classification;
Feature importance;
Decision trees;
Random forests;
Bagging;
Gradient boosting algorithm

**Corresponding author:*
jernej.mlinaric@ijs.si
(Mlinarič, J.)

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Izvirni znanstveni članek

Optimizacija zanesljivosti in hitrosti končnega nadzora kakovosti elektromotorjev z uporabo strojnega učenja

Mlinarič, J.[a,b,*], Pregelj, B.[a], Boškoski, P.[a], D,olanc, G.[a], Petrovčič, J.[a]

[a]Jozef Stefan Institute, Jamova cesta 39, 1000 Ljubljana, Slovenia
[b]Jozef Stefan International Postgraduate School, Ljubljana, Slovenia

POVZETEK

Dosledno ohranjanje vrhunske kakovosti izdelkov v proizvodnem procesu je izziv. Nadzor končne kakovosti mora biti zelo občutljiv, da zazna tudi najmanjša odstopanja, hkrati pa mora biti hiter in natančen. Vendar se sistemi za preverjanje kakovosti pogosto soočajo z zapleti pri kalibraciji, so dolgotrajni in v veliki meri odvisni od strokovnega znanja. Obdelujejo velike količine podatkov in pregledujejo številne lastnosti, od katerih nekatere minimalno prispevajo h končni oceni. Za reševanje teh izzivov so v članku predlagane metode strojnega učenja s statističnim nadzorom za klasifikacijo. Za izbiro lastnosti in natančno diagnozo, zlasti za razvrščanje elektromotorjev, so priporočeni klasifikatorji z odločitvenim drevesom, naključnimi gozdovi, zbirno učenje (angl. Bagging) in gradientno povečevanje. Z uporabo atributa pomembnosti lastnosti za izbiro lastnosti predlagani pristop primerja natančnost modelov ter znatno skrajša čas uvajanja in zagona. Študija je pokazala, da so vsi predlagani klasifikatorji dosegli visoko natančnost pri razvrščanju elektromotorjev v sistemu za nadzor kakovosti na koncu proizvodne linije. Poleg tega so učinkovito zmanjšali število lastnosti in optimizirali delovanje podatkovne baze. Uporaba zmanjšanega nabora funkcij je racionalizirala diagnostične algoritme, pospešila učenje in izboljšala razumljivost modelov, kar je povečalo splošno učinkovitost in preglednost. Poleg tega bi lahko analiza atributa pomembnosti lastnosti poenostavila diagnostično strojno opremo in pospešila nadzor kakovosti z odpravo nepotrebnih korakov. Z novo ustvarjenimi modeli se lahko preverijo tudi strokovne odločitve o izbiri elementov in prilagoditvah mejnih vrednosti, s čimer se poveča učinkovitost proizvodnih procesov.

PODATKI O ČLANKU

Ključne besede:
Nadzor kakovosti;
Odkrivanje napak;
Strojno učenje;
Izbira značilnosti in klasifikacija;
Pomen lastnosti;
Odločitveno drevo;
Naključni gozdovi;
Zbirno učenje;
Algoritem gradientnega povečevanja

**Kontaktna oseba:*
jernej.mlinaric@ijs.si
(Mlinarič, J.)

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