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A transfer learning approach to machine learning-based end-of-line quality inspection

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ABSTRACT

Transfer learning is a powerful machine learning technique for accelerating the learning process of a new classification task by using knowledge from an existing and related classification task that has already been trained. This technique addresses situations where the necessary training and test data are unavailable or where data acquisition is costly, difficult, or impractical. Additionally, transfer learning significantly reduces training time compared to training from scratch. This study demonstrates the benefits of transfer learning in developing an end-of-line quality inspection system to produce brushless DC electric motors during preproduction. Decision Tree, Random Forest, Bagging, and AdaBoost classifiers were trained on a dataset of 10,000 instances from a mass-produced motor subtype (A). Knowledge in the form of hyperparameters and feature importance was transferred to classifiers for two preproduction subtypes (B and C), each with only 100 instances. The results show up to a 20 % improvement in classification accuracy and significantly lower misclassification costs when using transfer learning. The study highlights the importance of transfer learning as an effective approach for improving industrial classification tasks, especially in preproduction phases where datasets are typically small and imbalanced.

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