THE FORMULATION OF A TRANSFER LEARNING PIPELINE FOR THE CLASSIFICATION OF WAFER DEFECTS

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I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Universiti Malaysia Pahang Al-Sultan Abdullah or any other institutions.

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ABSTRAK

Dalam proses pembuatan semikonduktor, wafer semikonduktor mungkin mempunyai kecacatan yang tidak boleh diterima kerana kerumitan dalam proses pembuatan. Pengesanan kecacatan dalam wafer adalah penting untuk mengelakkan kecacatan dalam kualiti produk akhir dengan menggunakan mikroskop optik. Ini sering menyebabkan salah penilaian dan keputusan tidak konsisten. Proses secara automatik telah digunakan pada dewasa ini mesin menggunakan algoritma pemprosesan imej. Walau bagaimanapun, kesukaran dalam menyediakan parameter yang diperlukan untuk algoritma pemprosesan imej menggalakkan penyiasatan dalam menggunakan klasifikasi pembelajaran dalam dalam mengesan kecacatan wafer. Klasifikasi pembelanjaran dalam boleh mendapatkan keputusan yang bagus dan mantap, tetapi unsur-unsur seperti kekurangan data dan kesukaran pelarasan hyperparameter menyebabkan perlaksaannya sukar dalam industry ini. Pembelajaran pemindahan digunakan untuk mengalihkan parameter dari model lain, menghasilkan keputusan yang sama bagus tapi lebih cepat dan mudah untuk melaksanakan.Sehingga kini, kajian yang terhad menyiasat klasifikasi kecacatan wafer menggunakan pembelajaran pemindahan gabung dengan pembelajaran mesin. Oleh itu, kajian ini akan bertujuan untuk meneroka 17 model pembelajaran pemindahan yang berbeza, dan mengklasifikasikan imej menggunakan 3 algoritma pembelajaran mesin berbeza, iaitu Support Vector Machine (SVM), k-Nearest Neighbor (kNN) dan Random Forest (RF). Pengelas pembelajaran mesin akan dinilai melalui teknik “5-fold cross validation” melalui carian grid. Imej akan dibahagikan kepada nisbah berstrata 60:20:20 sebagai data latihan, pengesahan dan ujian. Gabungan berbeza pembelajaran dalam dengan pembelajaran mesin akan dinilai dan dibandingkan untuk mendapatkan gabungan berprestasi terbaik melalui pelbagai ukuran prestasi seperti ketepatan, matriks, kepekaan dan skor F1. Telah diperhatikan bahawa model ResNet101v2 berpasangan dengan pembelajaran SVM mampu mencapai ketepatan terbaik sebanyak 95% untuk data latihan, data pengesahan dan data ujian.

ABSTRACT

In a semiconductor manufacturing process, a semiconductor wafer may have defects which are unacceptable due to its complexity in manufacturing process. Defect detection in wafer is vital in avoiding yield loss in end product, which is often achieved by visual judgement using an optical microscope. This often causes misjudgment and inconsistency result between different personnel. Automated processes have been used commonly in recent years, with the judgement done by using conventional image processing algorithm. However, limitations such as robustness and difficulty in setting up the parameters required for image processing algorithm encourages the investigation in using Deep learning classification in detecting the wafer defects. Deep learning classification produces excellent and robust results in classifying defects in wafer images, but challenges in data scarcity and hyperparameter tuning hampers its implementation in the industry. To combat this challenge, Transfer learning (TL) is investigated to utilize pre-trained weights from other models, which in turns produces similar excellent results while improving the efficiency of implementation. Thus far, there are still limited studies that investigate the classification of wafer defects using TL combined with a classical Machine learning (ML) pipeline. Thus, this study will aim to explore 17 types of TL models, and classify the features extracted using 3 different ML algorithms, namely Support Vector Machine (SVM), k-Nearest Neighbor (kNN) and Random Forest (RF). The ML classifiers were tuned via a 5-fold cross-validation technique through grid search approach. The input images were split into a stratified ratio of 60:20:20 ratio as training, validation and testing set respectively. Different combinations of TL-ML pipeline were evaluated and compared to obtain the best performing pipeline by various performance measures such as the classification accuracy, confusion matrix, precision, sensitivity and F1 score. It is observed that the ResNet101v2 model pairing up with an optimized SVM pipeline is able to achieve the best classification accuracy of 95% for training, validation and testing data.

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