

CLASSIFICATION OF RAIL DEFECT BASED
ON B-TYPE DISPLAY IMAGE USING DEEP
LEARNING METHOD

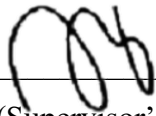
LI JIE

MASTER OF SCIENCE

UNIVERSITI MALAYSIA PAHANG

SUPERVISOR'S DECLARATION

I hereby declare that I have checked this thesis and in my opinion, this thesis is adequate in terms of scope and quality for the award of the degree of Master of Science.



(Supervisor's Signature)

Full Name : DOH SHU ING
Position : ASSOCIATE PROFESSOR
Date : 16/06/2023



STUDENT'S DECLARATION

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 or any other institutions.

A handwritten signature in black ink, appearing to be 'LI JIE', is written above a horizontal line.

(Student's Signature)

Full Name : LI JIE

ID Number : MAH21011

Date : 03/06/2023

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USING DEEP LEARNING METHOD

LI JIE

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ABSTRAK

Pengesanan kerosakan rel merupakan kaedah utama untuk memastikan pengangkutan kereta api selamat. Ketersediaan maklumat kerosakan rel membolehkan jabatan kereta api menentukan integriti rel keluli dan menyediakan pelan yang sesuai dalam proses pengoperasian dan penyelenggaraan kereta api. Bagaimanapun, pengesanan kerosakan rel pada masa kini masih bergantung kepada kaedah tradisional yang memerlukan intensiti tenaga kerja yang tinggi dan memakan masa. Tenaga kerja sedia ada tidak dapat menampung keperluan industri kereta api yang semakin meningkat. Tambahan pula, kaedah tradisional ini terdedah kepada kesilapan yang boleh mengurangkan ketepatan proses pengesanan kerosakan. Oleh itu, kajian ini bertujuan untuk mencadangkan kaedah pengecaman automatik berdasarkan pembelajaran mesin dan pemprosesan imej bagi menyediakan proses pengesanan kerosakan yang lebih cekap dan mampan di samping mengurangkan keperluan tenaga kerja yang tinggi. Untuk mencapai matlamat tersebut, objektif-objektif kajian adalah untuk: (1) Untuk mengklasifikasikan kerosakan rel keluli dengan menggunakan tenaga manusia; (2) Untuk membangunkan model pembelajaran mendalam untuk mengklasifikasikan kerosakan rel keluli berdasarkan imej paparan jenis B; dan (3) Untuk mengoptimumkan model pembelajaran mendalam dengan variasi yang berbeza. Dalam fasa 1, sejumlah 6000 imej kerosakan rel telah dikumpul dari Jabatan Kereta Api China Railway Hohhot. Kerosakan keluli tersebut telah diklasifikasikan dan dikenalpasti. Dalam fasa 2, model ResNet50 dibangunkan untuk pengesanan dan pengelasan kerosakan rel keluli. Kajian ini menggunakan 5000 imej kecacatan rel keluli sebagai data latihan untuk melatih model ResNet50, dan kemudian menggunakan 1000 imej rel keluli sebagai data ujian untuk mengesahkan struktur model. Dalam fasa 3, ResNet50 yang baru dibangunkan dioptimumkan dengan mengubah nilai parameter rangka kerja model, 14 keputusan analisis data akhir akhirnya diperolehi. Analisis kesesuaian dan penumpuan keputusan data menunjukkan model ResNet50 boleh memperoleh hasil yang optimum pada Epoch11. Kajian ini mendapati ketepatan keseluruhan model ResNet50 yang dicadangkan adalah 100% dalam set data ujian dan masa pengesanan satu imej kerosakan adalah 156 ms/imej, manakala baki tiga kaedah pembelajaran mendalam lain iaitu GoogleNet, VGGNet dan AlexNet semuanya mencapai ketepatan <95 %. Keputusan perbandingan menunjukkan bahawa model ResNet50 yang dicadangkan berpotensi untuk digunakan pada pengenalanpastian automatik dan klasifikasi kerosakan rel berskala besar.

ABSTRACT

The rail defect detection is the main method to ensure that the railway transportation is safe. The availability of rail defect information enables the railway departments to determine the integrity of the steel rail and provide suitable plans for railway operation and maintenance. However, the current rail defect detection still relies on the traditional method which require high manpower intensity and time consuming. The high manpower at the current state is unable to cater for the growing need of the railway industries. Furthermore, the traditional method is prone to errors and mistake which reduces the accuracy of the defect detection process. Therefore, this study aims to propose an automated recognition method based on machine learning and image processing to provide more efficient defect detection process while reducing the need of manpower. To achieve that aim, the objectives are to: (1) To classify the steel rail defect by using manpower; (2) To develop deep learning models to classify steel rail defect based on B-type display image; and (3) To optimize deep learning models with different variations of epoch. In phase 1, a total of 6000 rail defect images has been collected from China Railway Hohhot Railway Department. The defects were classified and identified. In phase 2, a newly developed model ResNet50 has been developed for steel rail defect identification and classification. This study uses 5000 steel rail defect images as training data to train ResNet50 model, and then using 1000 steel rail images as testing data to validate model structure. In phase 3, the newly developed ResNet50 are optimized by varying the parameter values of the model framework, 14 final data analysis results were finally obtained. The analysis of the fit and convergence of data results shows that the ResNet50 model can obtain optimal results at Epoch11. This study found that the overall accuracy of the proposed ResNet50 model was 100% in the test dataset and the detection time of a single defect image was 156 ms/ image, while the remaining three deep learning GoogleNet, VGGNet and AlexNet methods were <95%. The comparative results show that the proposed ResNet50 model has the potential to be applied to the automatic identification and classification of large-scale rail defects.

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LIST OF ABBREVIATIONS

ETR	Elettro Treno Rapido
TGV	Train à Grande Vitesse
CRH	China Railway High-speed
EU	European Union
RCF	Rolling Contact Fatigue
NDT	Non-destructive Testing
CNN	Convolutional Neural Network

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