COMPUTER VISION INSPECTION OF COLD-FLOW CASTING DEFECT WITH NEURAL NETWORK

By

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Dean

STATEMENT BY THE AUTHOR

I hereby declare that this submission is my own work and to the best of my knowledge,
it contains no material previously published or written by another person, nor material
which to a substantial extent has been accepted for the award of any other degree or
diploma at any educational institution, except where due acknowledgement is made in
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ABSTRACT

COMPUTER VISION INSPECTION OF COLD-FLOW CASTING DEFECT WITH NEURAL NETWORK

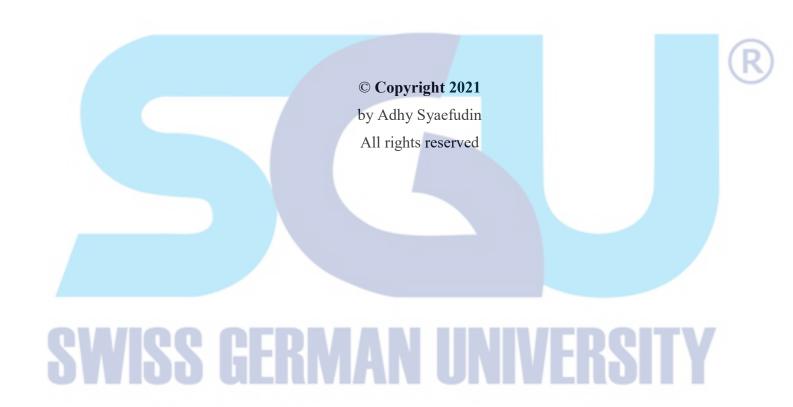
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The quality of the parts in the Aluminum High-Pressure Die Casting (HPDC) injection process is an important concern. If the defects that are not and sent to the next process will cause production cost loss, and can even result in losses in the hands of customers due to engine performance resulted from the part defects. The research thesis presents the implementation of object detection technology based on neural-network to detect cold-flow defect. Computer vision with neural network algorithm will be used to improve the result of visuals human inspections who have been detecting cold-flow defects that will t in aresul more stable and objective in carrying out quality assessments. This thesis will analyze the performance of the YOLOv5s framework in Pyhton. The analysis includes lighting conditions and the characteristics of the dataset. This thesis used cloud computing at Google-Colab during the training processof the Deep Convolutional Neural Network (DCNN), the computer specifications with graphic processing unit known as GPU (Tesla T4, 1.5 GB, 40 processor assigned by Google-Colab) are needed for the training process. The ROBOFLOW was very helpful tools in the dataset preparation phase of the development of this system. An intense discussion with the expert team was also performed, to make adjustments to the neural network object detection result. In conclusion, the developed system has proven to be very successful in assisting the HPDC part visual inspection.

Keywords: DCNN, neural-network, YOLO, ROBOFLOW, Python, computer-vision, object detection.



DEDICATION

I dedicate this thesis to Alloh, the god of the universe who has given me healthy and has obliged everyone to study. I hope I can contribute to the advancement of technology and education in my beloved country Indonesia.

I dedicate and give high gratitude to my beloved wife and my mother has encouraged me to continue my studies, for my children always make me smile and recharge my energy in the course of completion. And especially for my parents always pray for convenience in completing this study.

And finally I dedicate this thesis to my company, I hope it can always be agile and sustainable for the future.

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This master program with the existing curriculum and programs has opened my horizons, the logic of thinking, and an alignment between skills in the world of work with an academic framework.

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