

**HUMAN EMBRYO DEVELOPMENT ANNOTATION FOR  
CELL DETECTION USING CONVOLUTIONAL NEURAL NETWORK**

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11902010

BACHELOR'S DEGREE

in

Information Technology  
Engineering and Information Technology

SWISS GERMAN UNIVERSITY

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July 2021

**Revision after Thesis Defense on 15 July 2021**

## 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 the thesis.

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## ABSTRACT

### HUMAN EMBRYO DEVELOPMENT ANNOTATION FOR CELL DETECTION USING CONVOLUTIONAL NEURAL NETWORK

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*In-vitro* Fertilization (IVF) is a process that help couples who suffer from infertility and want to have a biological child. The process of IVF normally undergo external fertilization prior to embryo implantation to the mother's womb or uterus. Success rate of achieving clinical pregnancy after IVF program, however, remains lower in comparison to natural fertilization. Moreover, additional cost needed to undergo the IVF treatments is relatively expensive. One of the main problems contributing to the low IVF success rate is the lack of tools to precisely select the most viable embryo for transfer in embryology laboratory. Implementation of real-time embryo development monitoring through a time-lapse incubator is one of the promising technology to improve embryo selection. Utilizing a time-lapse incubator, embryologist allows to use several potential markers of embryo kinetics and its dynamic development obtained from time-lapse recording. Embryo annotation is one of the processes that need to be conducted to calculate the kinetics of embryo. This process remains conducted manually by the embryologist which potentially introduces bias that arises from individual subjective assessment. Part of the consideration is medical treatment of performing single elective embryo transfer is prioritized in IVF program, this research aims to do cell annotation for Hour 144 Embryo cells, starting from one-cell embryo

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(T1) to expanded blastocyst. Proof of concept from previous study has proven that cell annotation from T1-T4 is doable with the accuracy of 74%, this research will continue the annotation process of the previous study.

*Keywords: In-Vitro Fertilization, Embryo Annotation, Convolutional Neural Network. Image Processing*



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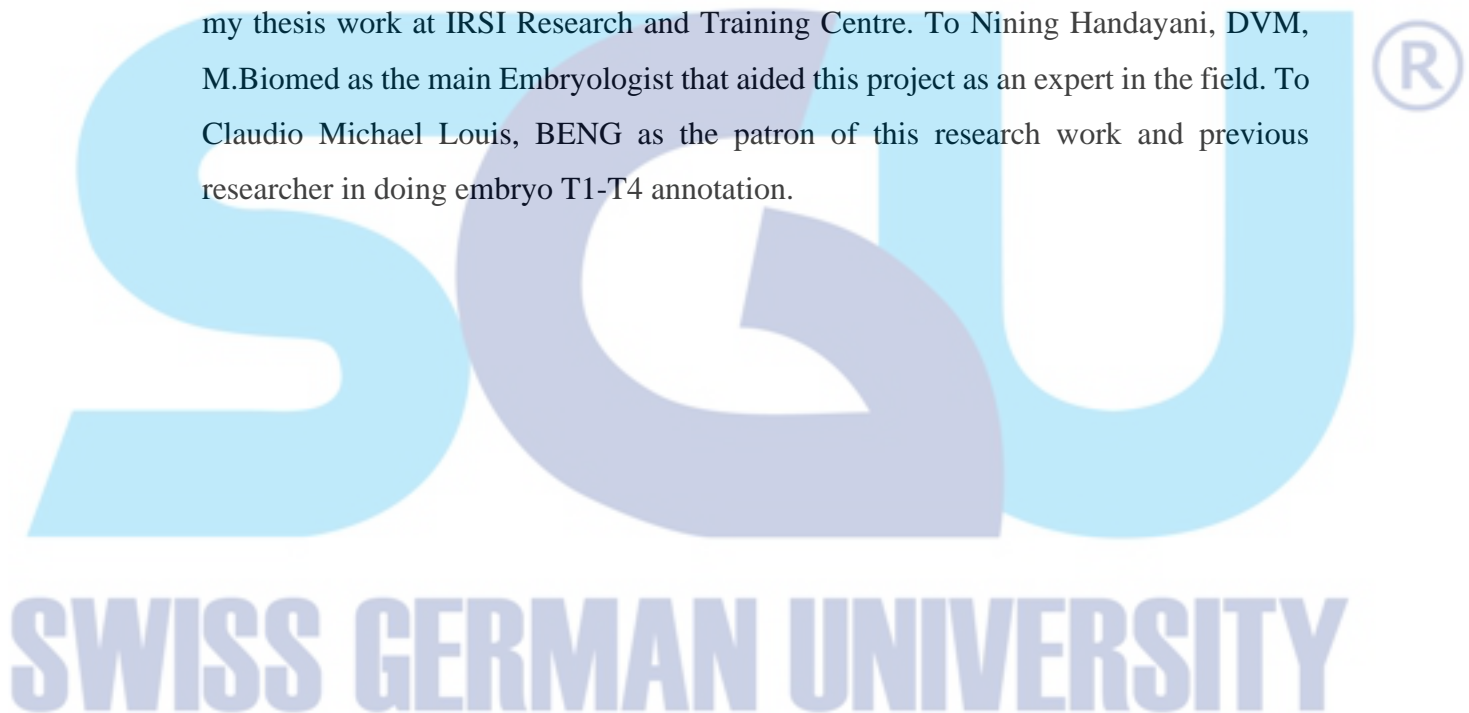
## DEDICATION

I dedicate this work to those who needed to undergo the In Vitro Fertilization process and medical personnel who are active in the following field. And those who have supported me throughout the whole research and writing process.



## ACKNOWLEDGEMENTS

To Alva Erwin as the main Advisor of my thesis work, I am deeply thankful for the guidance in doing my thesis work, giving me the opportunity, and introducing me to IRSI to conduct my thesis work. To James Purnama as the Co-Advisor of my thesis work, I am thankful for the guidance to oversee my thesis work and making adjustments to my thesis writing to make it appropriate writing. To Dr. Ivan Sini, MD, FRANZCOG, GDRM, MMIS, SpOG the Medical Director of Morula IVF Jakarta Clinic as the patron of this project. To dr. Arie A. Polim, D.MAS, MSc, SpOG (K) the director of the Indonesian Reproductive Science Institute (IRSI), I am grateful for allowing me to do my thesis work at IRSI Research and Training Centre. To Nining Handayani, DVM, M.Biomed as the main Embryologist that aided this project as an expert in the field. To Claudio Michael Louis, BENG as the patron of this research work and previous researcher in doing embryo T1-T4 annotation.



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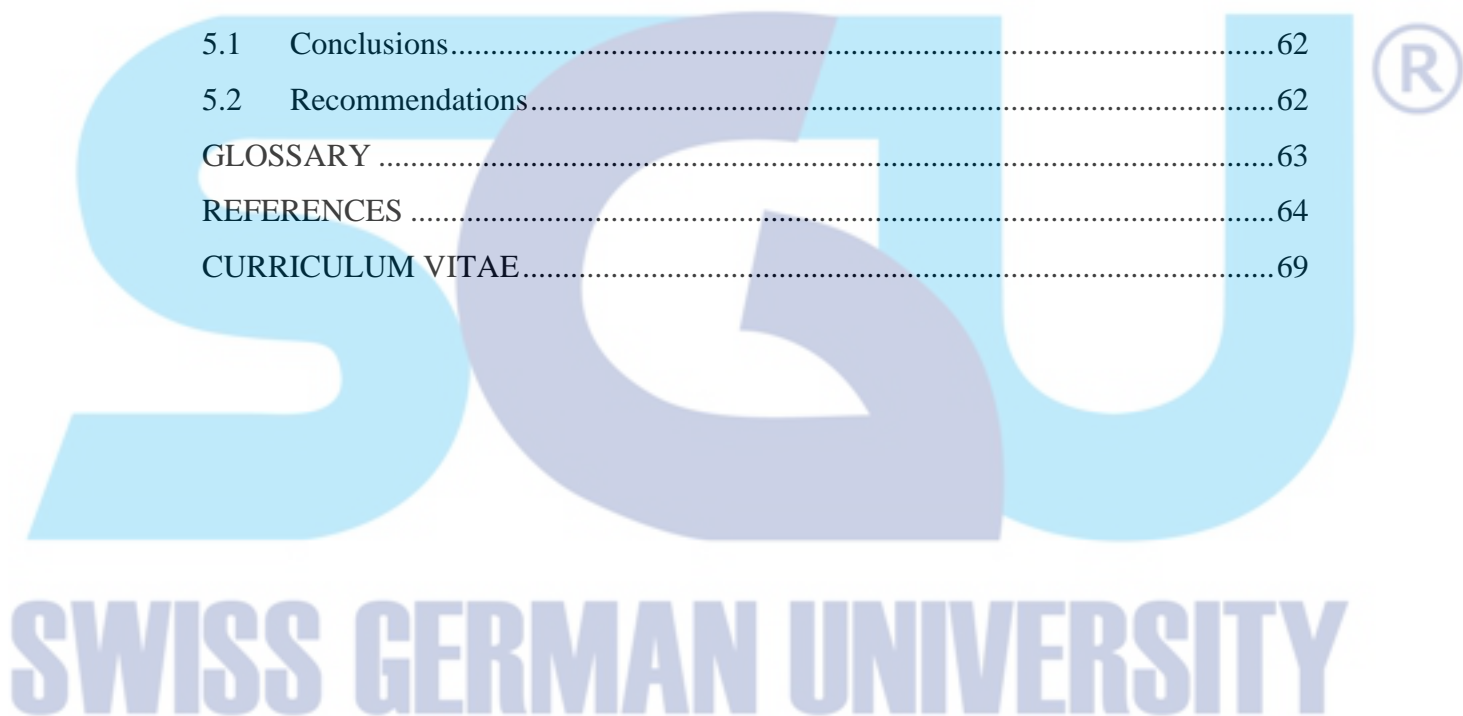
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