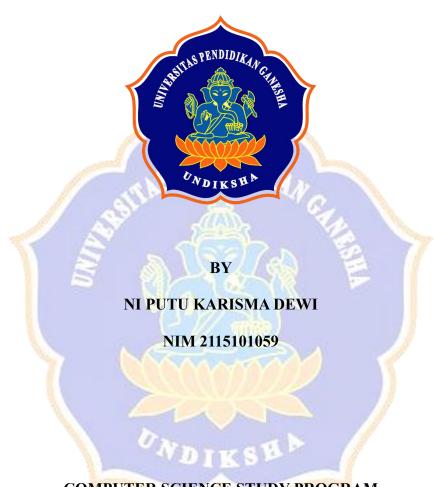
RIVER AREA SEGMENTATION USING SENTINEL-1 SAR IMAGERY WITH DEEP LEARNING APPROACH



COMPUTER SCIENCE STUDY PROGRAM
INFORMATICS ENGINEERING DEPARTMENT
FACULTY OF ENGINEERING AND VOCATIONAL
UNIVERSITAS PENDIDIKAN GANESHA
SINGARAJA

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RIVER AREA SEGMENTATION USING SENTINEL-1 SAR IMAGERY WITH DEEP LEARNING APPROACH

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Submitted to

Universitas Pendidikan Ganesha

To fulfill one of the requirements

In Completing the Bachelor of Computer Science Program

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I hereby declare that the written work entitled "River Area Segmentation using Sentinel-1 SAR Imagery with Deep Learning Approach" and all its contents are truly my own work and do not plagiarize and quote in ways that are not in accordance with the ethics applicable in the scientific community. With this statement, I am ready to bear the risk of sanctions imposed on me if later there is a violation of scientific ethics in my work or against claims to the authenticity of my work.

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PREFACE

I offer my deepest gratitude to God Almighty, for with His blessings, I have been able to complete this thesis to the best of my ability and on time. The title of my Bachelor Final Project is "River Area Segmentation using Sentinel-1 SAR Imagery with Deep Learning Approach."

This bachelor final project is submitted to fulfill the graduation requirements for the *skripsi* course in the Faculty of Engineering and Vocational Studies at Undiksha. This work would not have been possible without the support from people who have always assisted me, both morally and materially. My sincere gratitude goes to:

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I acknowledge that this bachelor final project still contains deficiencies that need improvement and further development. Therefore, I welcome constructive criticism and suggestions from all parties to refine this research report. I hope this bachelor final project will serve as a reference and guide that benefits relevant parties and readers in general.

Singaraja, 24 December 2024

Author

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