



# **Post Disaster Damage Assessment Model using Geospatial Data in the Satellite Images.**

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## DECLARATION

I hereby declare that the project work entitled Post Disaster Damage Assessment Model using Geospatial Data in the Satellite was submitted to the course Research Project, Sri Lanka Institute of Information Technology, was a record of an original work done by J. A. B. C. Kanchana, Under the guidance of Dr. Anuradha Jayakody, Supervisor of the project. The results in this report have not been submitted to any other university or institute for the award of any degree or diploma. This document is proprietary and exclusive property of the SLIIT. List of references I referred for the preparation of this document are given as references at the end of the document

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## Abstract

Natural disasters can happen without prior warning at any time. It is important to identify and analyse the post disaster situation to manage the disaster with quick response. Traditional approaches for disaster analyzing using field surveys are not suitable due to its high risk, time consuming, labor consuming and costly. In that case Satellite imagery data is ideal to use for identifying the disaster situation, risk mitigation and post disaster recovery because it's easy to get the data at anyplace, anytime. However, the processing of satellite imagery is a significant difficulty and identifying things in a satellite image is crucial in this field. By using satellite imagery with the newest technologies like the deep learning approaches can be used to identify the disaster area. Accuracy and efficiency are a very important factor for making damage assessments and providing relief services. This research focused at how deep learning can be used to assess building damage using satellite imageries. The objective of this research is to develop a building damage assessment model by using deep learning, which can be use in post disaster analysis. According to the literature survey encoder – decoder model and Siamese model used for process the pre and post disaster satellite images and assess the damage.

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