

**EXPLAINABLE SPATIO-TEMPORAL IMAGE
SEGMENTATION FOR MULTIVARIATE DATA: A
CASE STUDY ON PRECIPITATION
NOWCASTING**

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Degree of Master of Science

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University of Moratuwa
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DECLARATION

I declare that this is my own work and this Dissertation does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. I retain the right to use this content in whole or part in future works (such as articles or books).

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The supervisor should certify the Dissertation with the following declaration.

The above candidate has carried out research for the Degree of Master of Science Dissertation under my supervision. I confirm that the declaration made above by the student is true and correct.

Name of Supervisor: Prof. Dulani Meedeniya

Signature of the Supervisor:

Date: 19/06/2024

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ABSTRACT

Artificial Intelligence (AI) systems are often considered black boxes, making it difficult to understand the region of interest in the input for the classification and decision-making processes. This creates a challenge in convincing people who rely on traditional methods to trust the outputs of these systems. While there have been efforts to develop explainable AI systems for general machine learning problems, the same cannot be said for complex datasets such as the datasets used in precipitation nowcasting. In this paper, we adapt and apply existing Integrated gradients methods to understand and explain the predictions made by a deep learning model for precipitation nowcasting which takes a multi-image sequence as its input. We use the Meteonet dataset by MeteoFrance and form it into a spatiotemporal multivariate dataset consisting of rain radar, satellite, and wind images to predict rainfall 30 minutes ahead. We employ the U-Net model and evaluate the model's explainability using Integrated gradients. The best performance achieved is an F1 Score of 0.76, consistent with other research using the same dataset. This lays a solid foundation for evaluating explainability. Our results show that this can not only explain the model predictions but also provide a visual representation of why the predictions were made, offering a potential solution for any spatio-temporal or multivariate dataset. Additionally, since this method provides a comparative analysis of how much each image in the input sequence contributed to the final result, we demonstrate how the same method can be further used for dimensionality reduction, enhancing the interpretability and efficiency of the predictive model.

Keywords: Artificial intelligence, integrated gradient, U-Net, satellite, precipitation, nowcasting

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LIST OF ABBREVIATIONS

Abbreviation	Description
2D	two dimensional
AI	Artificial Intelligence
CNN	convolutional neural network
DL	deep learning
EUMETSAT	European Organisation for the Exploitation of Meteorological Satellites
GAN	Generative Adversarial Networks
GIG	Guided Integrated Gradients
GPM	Global Precipitation Measurement Mission
GRAD-CAM	Gradient-weighted class activation mapping
IG	Integrated Gradients
IG2	Iterative Gradient path Integrated Gradients
LSTM	Long short term memory
NWP	Numerical Weather Prediction
ROVER	Real-time Optical Flow by Variational Methods for Radar Echoes
XAI	Explainable Artificial Intelligence

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