Early Bushfire Detection Using Environmental Monitoring Sensing and Deep Learning Approach

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Introduction

Bushfires present a severe and growing threat, especially in Australia where they cause widespread destruction and environmental damage. [1]

Early detection systems are crucial for minimising the impact of these fires. This project focuses on the development of a real-time bushfire detection system using environmental sensors and advanced machine learning models. These models aim to identify anomalies in environmental data that may indicate the presence of a bushfire, allowing for timely alerts and interventions.

Methodology

- The project focus on the algorithm part running on the server of the wireless sensor network (WSN) to provide real-time judgements. [2]
- The dataset was collected from controlled burn experiments, capturing environmental readings like temperature, humidity, eCO2, and TVOC. Multiple sensors were deployed around the fire source.
- Due to the unavailability of data labels, the challenge is categorised as an anomaly detection problem. The dataset will be classfied into either "Fire" or "Normal" condition

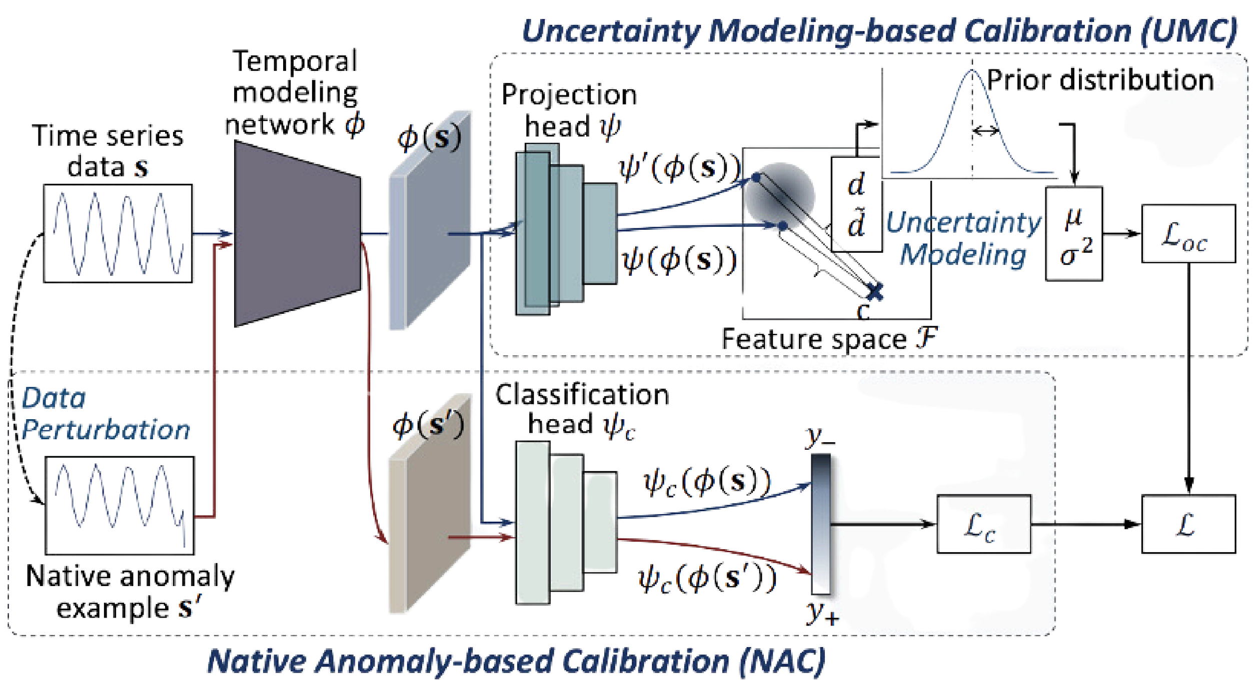

Fig.1. The framework of the COUTA model [3]

- We applied the state-of-the-art anomaly detection model **COUTA** (Calibrated One-class classification-based Unsupervised Time series Anomaly detection), which is an unsupervised learnging method leveraging Uncertainty Modelling-based Calibration (UMC) and Native Anomaly-based Calibration (NAC).

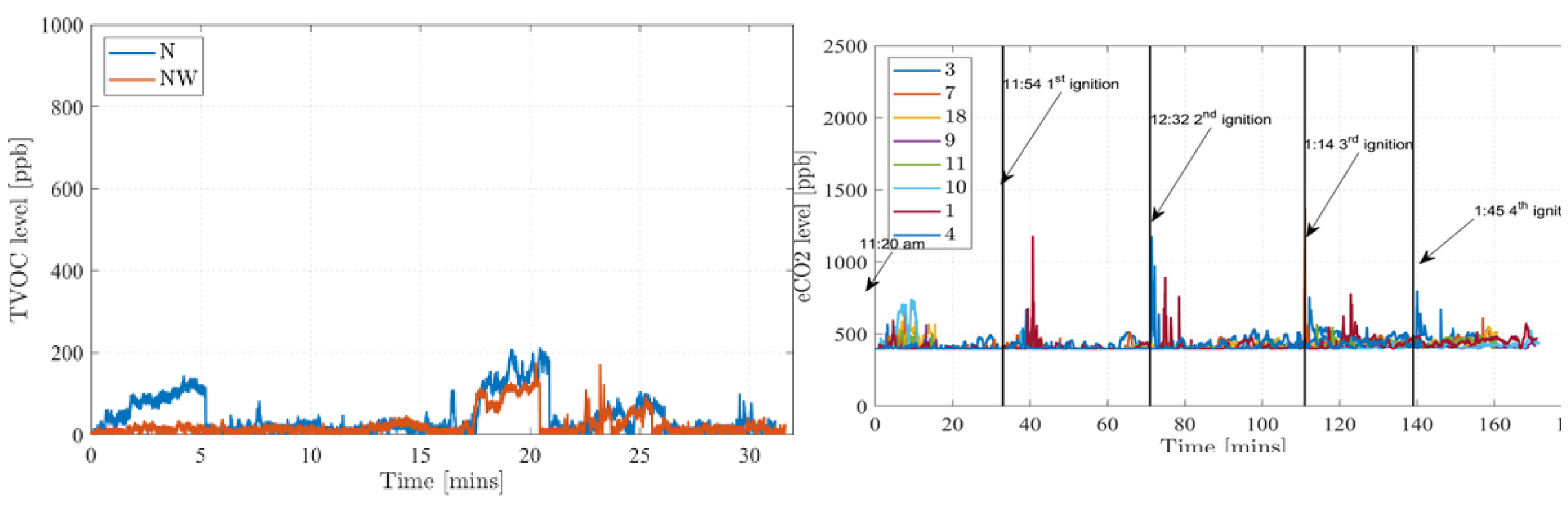

Fig.2. The training dataset (normal condition) and the testing dataset

- The model is trained on normal data and calibrated to detect outliers that might indicate a fire in the experimental burn condition.
- The loss function L = L(UMC) + αL(NAC)

ACTUAL VALUES	POSITIVE	NEGATIVE
POSITIVE	TP	FN
NEGATIVE	FP	TN

$$Precision = \frac{TP}{TP+FP} \qquad Recall = \frac{TP}{TP+FN}$$

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN}$$

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

- Since in the real scenario, the fire condition is rare. So a trivial guess of "Normal" may reach an accuracy of over 99%, however missing the most important fire stage makes the detection function in vain. So in the evaluation method, we stressed on precision rather than accuracy.

Results

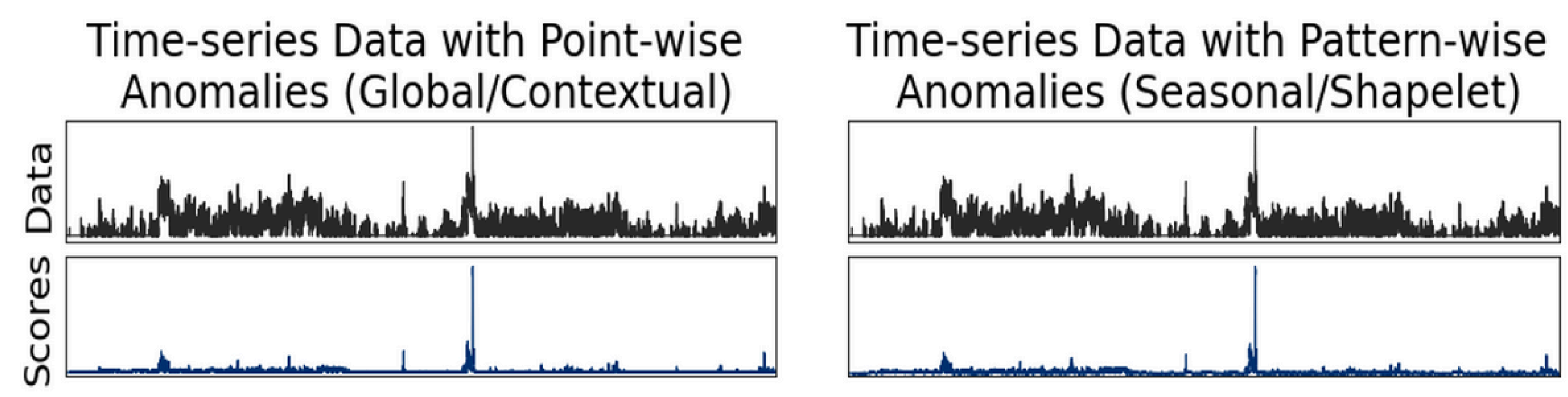

Fig. 3. The detection result of the training dataset

- No anamoly is detected in the training dataset, which means the training accuracy and precision both reached 100%

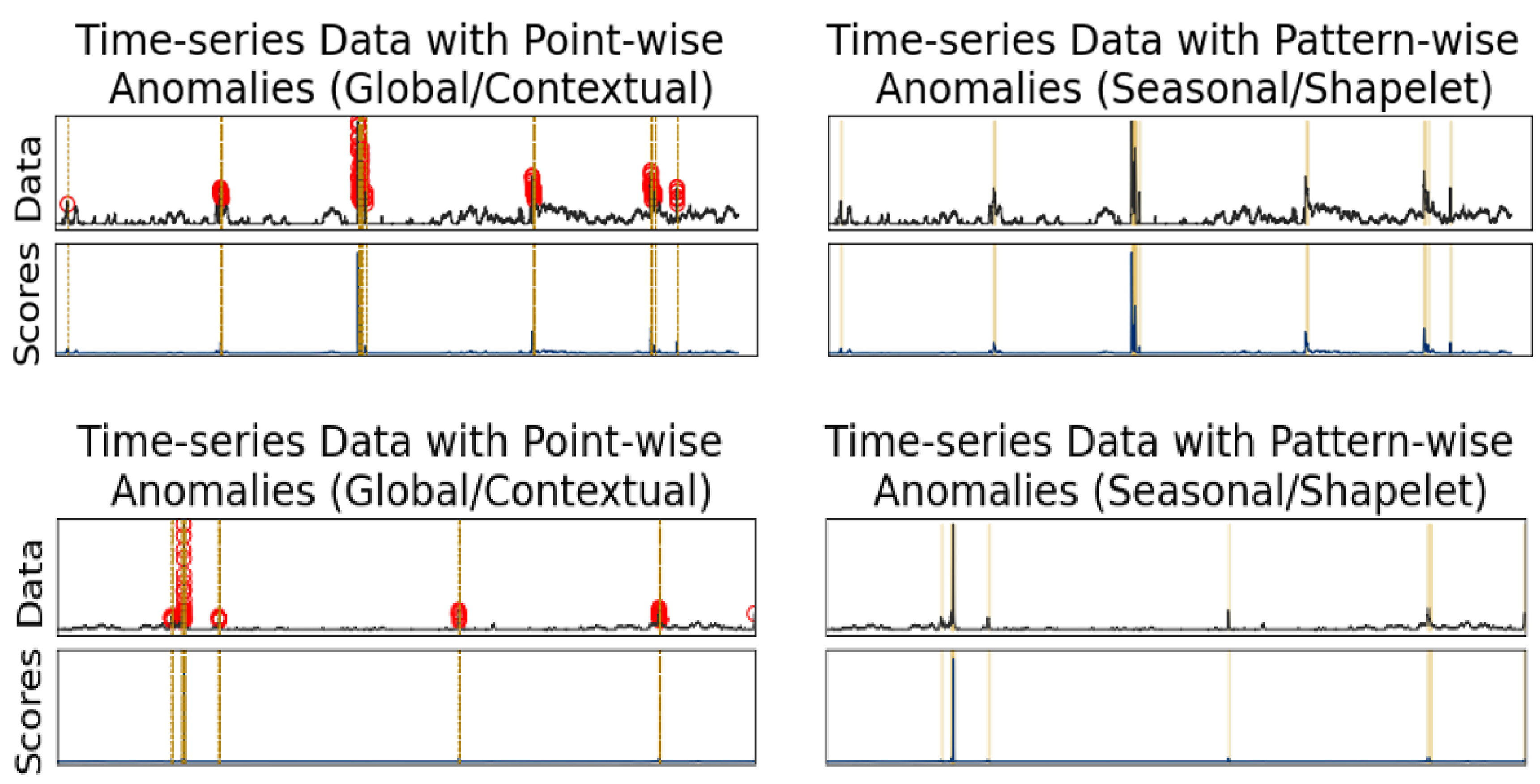

Fig. 4. The combined result of the testing dataset from multiple sensors around the fire source

- If the detection time aligns closely with the ignition time, which we defined as within a 10-minute window for our study, we conclude that the algorithm has captured the fire and it is true positive.
- Based on point-wise anomaly analysis, the model achieved over 88% precision, providing a robust and reliable solution with minimal false alarms.
- By integrating data from multiple sensors, the model ensured that no fire events were overlooked while maintaining an acceptable detection delay.

Conclusion

In this project, we successfully implemented a real-time fire detection model using the COUTA framework, which provided both pattern-wise and point-wise anomaly detection.

The model demonstrated strong performance with over 88% precision, ensuring a low false alarm rate and no overlook on any fire event. Additionally, a thorough analysis was conducted to understand and address factors affecting the system's stability, further enhancing its reliability for real-world applications.

Reference

[1] A. D. L. C. W. S. L. Hughes, M. Rice and G. Mullins. "SUMMER OF CRISIS." https://www.climatecouncil.org.au/resources/summer-of-crisis.

[2] WTWH Media LLC. "Wireless Sensor Networks (WSN) : IoT Part 34." https://www.engineersgarage.com/wireless-sensor-networks-wsn-iot-part-34

[3] Y. W. H. Xu, S. Jian, Q. Liao, Y. Wang and G. Pang, "Calibrated One-class classification-based Unsupervised Time series Anomaly detection," arXiv preprint, vol. arXiv:2207.12201, 2022, doi: arXiv.2207.12201.

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