University of Wollongong

Edge-Based Federated Learning for Bandwidth-Efficient Wildlife and Bushfire Monitoring in Remote Australian Environments

Research Proposal — Master of Research (IT / Computer Science)

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Intended Degree: Master of Research

Discipline / Area: Artificial Intelligence, Edge Computing, Federated Learning

Proposed Supervisors: (To be confirmed)

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Introduction/Background

Australia's unique biodiversity boasts 80% of its mammals and 90% of its reptiles as endemic, but many species are increasingly endangered by habitat loss, invasive predators, and extreme bushfire events. The infamous 2019-2020 “Black Summer” bushfires killed or displaced an estimated three billion animals (WWF Australia, 2020). One outcome of this tragedy is a heightened awareness of the need for effective, real-time environmental monitoring of Australia's extensive remote regions. Current approaches are inadequate: wildlife surveys have a low frequency and are labor-intensive while remote camera traps generate extensive image data with around 90% being trigger images without the target wildlife (Bruce et al., 2025). Sending high-resolution images from the outback via satellite is prohibitively expensive (in the order of hundreds of dollars per gigabyte) while physically retrieving data (e.g. memory card swapping) introduces delays of weeks. These limitations on data processing capability prevent timely reactions to invasive predators, endangered species decline or ignitions of new bushfires.

Bushfire monitoring in remote areas relies on public detection or sporadic satellite image capture so small ignitions go undetected until they grow large. Thus, real-time monitoring in remote Australia is lacking and represents a critical detection gap. Existing systems of detection warning are in need of fundamental redesign to facilitate real-time monitoring that is bandwidth efficient even when operating with low connectivity. Edge computing and federated learning provides an ideal basis for a solution (Miller et al., 2025). Based on this background, the research question guiding this project proposes a hierarchical, edge-based federated learning solution for accurate, low-bandwidth wildlife monitoring and bushfire detection in remote Australian regions.

Research Questions

Primary Research Question: How can a top-down, edge-based, federated learning architecture be designed to provide accurate wildlife and bushfire detection for bandwidth-limited, privacy-preserving, remote Australian environments?

Secondary Research Questions:

- How effectively can a hierarchical aggregation scheme and non-IID–aware FL algorithms (e.g. FedProx) mitigate model divergence caused by heterogeneous ecological data?
- What trade-offs exist between detection accuracy, energy consumption, and thermal stability when deploying lightweight computer vision models on edge hardware?
- To what extent can a hierarchical FL approach reduce satellite data transmission costs compared to a centralized model?

- How can the federated learning system design align with the CARE Principles for Indigenous Data Governance?

Purpose & Aims

The proposed research seeks to create, develop and test a decentralised intelligent remote monitoring system for environmental observation. The system will decentralise passive remote sensors and turn them into intelligent agents that operate independently and in the peer-to-peer network to collaboratively improve their models for real-time wildlife (e.g. identifying a wallaby instead of a feral cat) and early bushfire detection, without human intervention, data being sent, or raw data uploads. By using on-device federated learning, it would minimize communication expenses without significantly decreasing detection accuracy for wildlife and bushfire events of interest. Such need directly addresses Australia's need for remote sensing systems that can detect wildlife threats quickly and provide early bushfire alerts in an area where connectivity is often poor or non-existent.

Specific Aims:

- **Design** a hierarchical federated learning architecture combining edge devices, regional gateway aggregators, and a cloud coordinator.
- **Optimize** lightweight computer vision models (e.g. YOLO variants) for on-device inference and federated training.
- **Evaluate** bandwidth usage, model accuracy, and energy efficiency through a simulation-based “digital twin” of remote deployments.
- **Ensure** ethical data governance by keeping raw ecological data local (aligning with Indigenous data sovereignty principles).

Significance

Proposed edge-based FL will also better minimize response times to biodiversity and fire threats than current systems. Where (human) data collection weeks later reveals a problem, field camera traps can alert park managers to invasive predators or small fires before they've had a chance to spread. Moreover, such information can prevent biodiversity losses and small, smoldering efforts from becoming raging infernos. This is possible because FL minimizes the need for proactive, constant monitoring over large, remote spans. Thus, this project, in particular, supports national conservation efforts, such as Australia's *Threatened Species Action Plan 2022-2032*.

Technically, it overcomes longstanding remote monitoring challenges of connection and cost. For image data to be sent to satellites to be processed is expensive and currently applicable to only small-scale camera networks. Federated learning requires less communication, as it sends only model updates instead of raw data, which saves in bandwidth usage and preserves detection capabilities. This means camera networks can be solar or battery powered - low-energy requirements - where Green AI taught low-carbon computing allows massive sensor networks to be privacy-preserving and achievable with efficient practices.

Finally, strategically, everyone is connected for AI training but the data does not leave the camera to which it is sent and processed, meaning existing environmental data networks (TERN, Atlas of Living Australia) can compile data without central database weaknesses. Utilizing CARE Principles for Indigenous Data Governance means that Indigenous data sovereignty is respected, limiting privacy violations (Carroll, S. *et al.*, 2020). Therefore, this study validates a feasible solution to ethical scaling with federated edge computing AI for both federated edge computing and conservation in difficult field settings.

Literature Review

Wildlife Monitoring: Camera trap investigations across Australia create massive image libraries, but due to the fact that up to ~90% of images are null (false trigger) data, sifting through the desired research data becomes cumbersome (Bruce et al., 2025). Deep learning has transformed automated species identification to the level of human efficacy—if not better—but most applications involve cloud-based processing. This does not align with researchers operating in remote regions with low bandwidth (Mulero-Pázmány et al., 2025). Thus, this article investigates whether there are any methods to resolve the issues of onsite identification and null data filtration instead of sending null images to the cloud for processing.

Bushfire Detection: The same issue arises for bushfire detection. Ground sensors are not highly sensitive enough to detect small ignitions far away in country or rural areas, forests. The most recent application of IoT sensor networks with federated learning for decentralized fire detection networks suggests that decentralized awareness options will help with timeliness of detection (Abdul Salam et al., 2025). Yet much of the literature suggests wildfires *or* wildlife independently and under connected, low frequency opportunities. This paper builds off the literature by simultaneously detecting wildlife and fire in one federated system as the approach taken to federated learning in the literature review only connects for different levels of data collection by means of low-bandwidth, and was tailored for specific situations.

Federated Learning Algorithms: However, typical FL algorithms are not reliable in the face of non-IID client data and communication limitations. For instance, sensor data across regions are often extremely heterogeneous which is causative for client drift and reduced convergence speed (Xia et al., 2021; Jimenez et al., 2024). For instance, **FedProx** uses a term of regularization to better fit data differences and a series of methods of update compression (sparse gradients or quantized gradient transmission) are applied to reduce the amount of communication needed. Thus, we will build off of these findings through the use of a hierarchical FL system and algorithms that are otherwise stable under non-IID conditions to stabilize models in spite of real-world discrepancies.

Edge AI and Communication Constraints: With edge AI developments, small-sized vision models with low-latency performance run even on low-power processors. For instance, YOLO-Nano is an object detector usable for fast inference in embedded devices with decent performance accuracy (Wong et al., 2019). However, little is known about the performance of such models within a federated learning system for complicated classes in the field with real-world constraints. Furthermore, remote sensors operate using long-distance wireless connections (LoRaWAN, for example) that have extremely low data rates, meaning extreme bandwidth preservation is needed. For example, previous work establishes that a hierarchical FL framework using intermediate aggregation entities (regional gateways) assists in significantly lowering the backhaul communication volume. These results are part of the justification for our system architecture, which fuses multiple levels of model aggregations and aggressive communication compression to suit low-bandwidth scenarios.

Methodology

Architecture: We will implement a **hierarchical federated learning** framework on edge devices for data generation, gateway aggregators for an intermediary (but still localized approach) and a cloud coordinator. This decentralized framework stems from theoretical explanations behind federated learning to alleviate communication limitations and non-IID data complications. Empirical system performance will be assessed via FL conventional metrics of success: model accuracy, speed of convergence, and communication overhead. In addition, the CARE Principles support an ethically sound system since the onset is that, due to the nature of the information, raw data will not leave the localized device. Therefore, this system supports high privacy requirements and IDC regulations.

Simulation: The research will mainly be evaluated through simulation with the Flower FL framework. A simulated *"digital twin"* of the sensor network will mirror the many virtual edge clients and federated learning experience. We will simulate the existing datasets (ex. wildlife images) into realistic, non-IID distributions by splitting datasets (Dirichlet-based splits will skew data amongst clients). The simulated network will be modified to accommodate the situations of the LoRaWAN connectivity—compromised bandwidth, increased latency—so that we can uniformly assess performance under differently heterogeneous data, variable numbers of nodes, and compromised network integrity.

Algorithm Evaluation: We will implement and evaluate federated learning methods: the baseline FedAvg algorithm, FedProx (to ensure better convergence in non-IID scenarios) and a federated hierarchical FL with intermediate aggregation at the gateway nodes. We will also implement communication-efficient approaches, like gradient compression or update sparsification to reduce the required bandwidth. We will evaluate model performance of each method based on accuracy, stability of training convergence and a data sent to assess the cost of accuracy versus efficiency.

Edge Hardware Testing: In order to test the system performance in realistic, operating conditions, we will deploy trained models on real edge hardware representative of the field devices (e.g. Raspberry Pi 5; NVIDIA Jetson Orin Nano) and measure inference latency, power consumption, and temperature management for extended, uninterrupted use on such devices. These findings will highlight constraints of the hardware (overheating, excessive draw of voltages, etc.) and inform us of necessary changes to the model in order for the solution to be feasible in a solar, off-grid powered setting.

Ethical & Compliance: The nature of the project is that all unprocessed sensor data remains on the local devices so no privacy concerns exist and Indigenous data sovereignty is upheld (no sensitive ecological data will ever leave the local device to go to a general, centralized server). Therefore, the very nature of our approach facilitates ethical data governance with standards like the CARE Principles. In addition, no wildlife or human intervention is planned as we will be using existing datasets for training and simulations—any future implementation in the field will apply for prior ethical approval.

Timeline

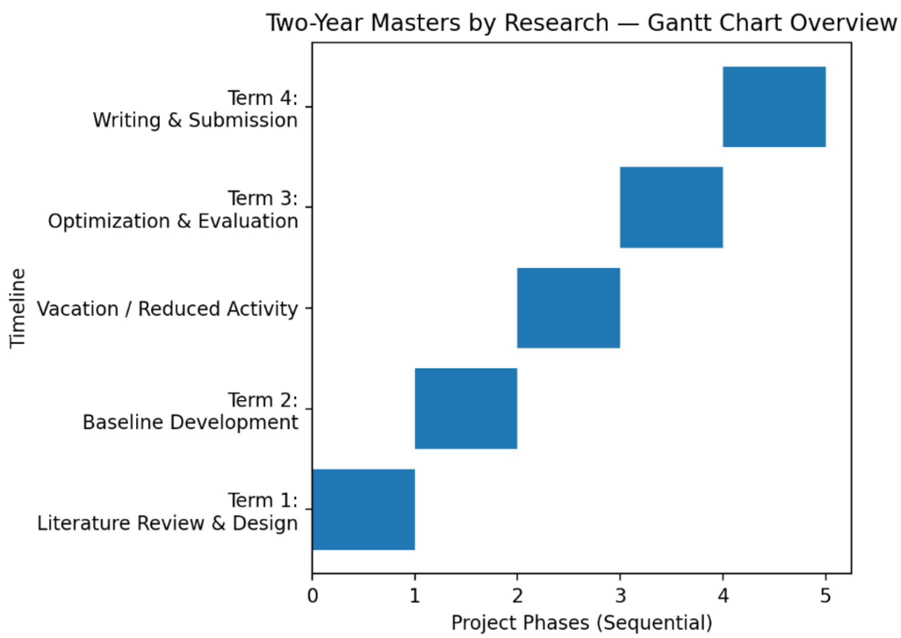

Figure: Gantt chart of the two-year research in accordance with the Master by Research arrangement.

The project is split into 4 terms with a vacation break at the end of term 2. The first term is dedicated to the literature review, refinement of research questions, preparation of the dataset and construction of the hierarchical federated learning architecture; the second term is dedicated to federated learning framework construction for initial experiments and baseline experiments; the vacation break acts to minimize experiments related to the research and allows for light reading, documentation and reconsideration of the project's scope. The project resumes in the third term with adjustment of performance tuning based on the algorithm, non-IID performance and system evaluation. Finally, the fourth term is dedicated to final experiments, thesis writing, article writing, revisions and submission.

Expected Outcomes

By the conclusion of this project, we expect to deliver the following outcomes:

- An **empirically validated hierarchical federated learning framework** for low-bandwidth wildlife and bushfire monitoring because of a series of prototypes/simulations.
- Qualitative findings (experimental results) that statistically **reduce transmission and energy expenditure** relative to a centralized equivalent with statistical significance.
- Real-world implications for **AI deployed ethically and data-sovereign** in ecological monitoring (i.e. proposed solutions are privacy-preserving and compliant with Indigenous data rights).
- Completed **Master's thesis** on the topic and at least one other peer-reviewed publication of findings.

Conclusion

This project proposes a realistic and ethical federated learning solution for wildlife and bushfire remote sensing. As edge intelligence with an ethical stance toward data privacy, this research will contribute a practical system for low-connectivity environments and valuable results to the fields of conservation and federated learning literature.

References

Abdul Salam, M., Badr, E., & Elbohoty, A., 2025. *Mayfly-based federated learning approach for early detection of fire*. **International Journal of Data Science and Analytics**, 20(8): 7167–7187.

Bruce, T. *et al.*, 2025. *Large-scale and long-term wildlife research and monitoring using camera traps: a continental synthesis*. **Biological Reviews**, 100(2): 530–555.

Carroll, S. *et al.*, 2020. *The CARE Principles for Indigenous Data Governance*. **Data Science Journal**, 19: 43.

Jimenez G., D.M. *et al.*, 2024. *Non-IID Data in Federated Learning: A Systematic Review with Taxonomy, Metrics, Methods, Frameworks and Future Directions*. **arXiv preprint**, 2024.

Miller, T. *et al.*, 2025. *Federated Learning for Environmental Monitoring: A Review of Applications, Challenges, and Future Directions*. **Sensors (MDPI)**.

Mulero-Pázmány, M. *et al.*, 2025. *Addressing significant challenges for animal detection in camera trap images: a novel deep learning-based approach*. **Scientific Reports**, 15(1): 16191.

Wong, A. *et al.*, 2019. *YOLO Nano: a highly compact "You Only Look Once" convolutional neural network for object detection*. In **Proc. 5th Workshop on Energy Efficient Machine Learning (NeurIPS 2019)**, pp. 22–25. IEEE.

WWF Australia, 2020. *After the catastrophe: Report on wildlife losses from the 2019–2020 bushfires*. **WWF Australia Report**.

Xia, Q. *et al.*, 2021. *A survey of federated learning for edge computing: Research problems and solutions*. **High-Confidence Computing**, 1(1): 100008.