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Deep Learning Wildfire Scenario Modelling: A Case Study for iFire 2.0 †

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Abstract

This study presents a deep learning–based wildfire behaviour model developed for iFire 2.0, an immersive visualisation project by iCinema, UNSW. The model integrates fuel conditions, ignition points, and weather conditions to simulate fire spread and crown fire activity. It demonstrates the ability to generate unforeseen dynamic scenarios under changing conditions, marking an important step toward modelling and visualising extreme wildfire behaviour, allowing users to modify variables and experience resulting changes in wildfire dynamics.

Keywords: wildfire behaviour modelling; deep learning; immersive visualisation

1. Introduction

Wildfires, especially extreme wildfires, cause irreversible damage to ecosystems, human lives and economies globally. iFire 1.0 at iCinema, UNSW, addresses the visualisation of traditional wildfires using a leading immersive visualisation system for firefighter training and academic purposes [1]. With rapid progress of artificial intelligence (AI), particularly deep learning (DL), iCinema launched iFire 2.0 in 2026 to develop data-driven wildfire scenario models trained on large datasets rather than relying solely on human expertise to picture the uncertainties of extreme fires.

This paper presents our DL model currently deployed in iFire 2.0. Based on our earlier design in [2], which considers only the terrain information and simulates fire spread, the deployed version incorporates ignition, fuel conditions, wind and temperature conditions to generate fire arrival, burnt area and crowning fire occurrence. We also present a case study using hypothetical pine plantation. The use of synthetic data allows controlled experimentation and large-scale sample generation, which is valuable during early-stage model development prior to real-world deployment and validation. We demonstrate that our DL model can successfully generate diverse extreme wildfire scenarios under varying conditions.

2. From iFire 1.0 to iFire 2.0

iFire 1.0 and 2.0, proposed by iCinema, UNSW, connect researchers worldwide through immersive 3D environments that support collaborative engagement with dynamic wildfire scenarios, including the Australian Black Summer fires of 2019–2020 and the Los Angeles fires of 2025.

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iFire 1.0 (2021–2025) transforms CSIRO SPARK wildfire simulations [3] of historical events into cinematic 3D scenarios using Unreal Engine 5, a technology widely used in the film and gaming industries. The platform visualises moderate- to high-danger fire conditions and focuses on scenarios that support anticipatory understanding and situational preparedness under moderate uncertainty [1].

iFire 2.0 (2026–2027) is expanding this capability by adopting a custom DL model trained on fire behaviour patterns. Compared to mathematical simulators, the DL model is fully data-driven, allowing it to rapidly generate large numbers of fire scenarios without the computational cost and time constraints typically associated with physics-based simulations and solving the underlying physics. Moreover, the DL model is extendable, enabling future improvement by integrating real-world fire patterns. This enables faster exploration of uncertainty, broader coverage of possible fire behaviours, and more scalable integration into operational planning and risk assessment workflows. By combining simulated fire dynamics with observed environmental conditions, iFire 2.0 aims to deliver more adaptive, responsive, and probabilistic fire intelligence for emergency management and decision support.

3. Test Cases

3.1. Pine Plantation Scenario

This hypothetical scenario represents a landscape comprising both grassland and pine plantations [4] and serves as the primary demonstration case in iFire 1.0. As shown in Figure 1 (fuel), the fuel map includes four classes: grassland, eucalyptus forest, and young and mature pine plantation. The spatial resolution is 3.84 m, with 2560 pixels. This scenario is well-suited to visualising differences in fire spread behaviour between grassland and pine plantation areas.

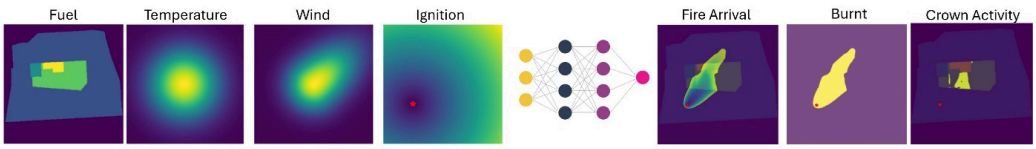


Figure 1. The inputs and outputs of the pine plantation case.

3.2. Dataset Construction

For each case, we construct the dataset by generating approximately 5000 fire spread simulations using the CSIRO Spark simulator [3] deployed in Spark 1.0 under varying wind and temperature conditions. Ignition locations are uniformly sampled across the geographic region of interest. Each simulation is run for six hours, after which the resulting fire arrival maps and crown activity maps are collected as ground-truth labels.

4. DL Model

We adapt a transformer-based semantic segmentation model (SegFormer [5]) to predict fire arrival, burnt area, and crown fire activity. As shown in Figure 1, weather variables are converted into raster maps: wind is represented as asymmetric Gaussian maps based on direction and speed, temperature as a Gaussian map scaled by temperature, and ignition as a distance transform from the ignition point. The outputs include a fire arrival map, representing the time when fire arrives on each pixel, and the burnt area, indicating whether the pixel is burnt. The crowning fire map is a binary map indicating whether burnt areas involve crown fire activity. To reduce GPU memory, input maps are resized to 512×512, while outputs are subsequently upsampled to 2560×2560.

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The model is trained for 200 epochs on 5K fire spread samples simulated using the CSIRO Spark simulator [3] with different wind and ignition conditions. Each sample is spread for six hours. To calculate the losses, we first normalise the fire arrival using a SoftPlus activation function, ensuring that each pixel has a positive value. The model is optimised using the mean squared error loss. Meanwhile, we mask out unburnt regions during loss computation, reducing training complexity by excluding unburnt areas from consideration. For burnt area and crowning fire, the losses are calculated using a binary-cross-entropy function with a Sigmoid activation.

5. Results and Discussion

We first test our model on 750 simulated samples using the evaluation metrics used in our test scenario, where the fire arrival achieves 88.1% of IoU_all and 80.4% of MIoU scores, while the crowning activity achieves 23.1% of IoU_all.

Figure 2 shows the fire spread and crowning behaviours in the testing samples, illustrating that the model can generate diverse fire patterns under different input conditions, including ignition locations, wind conditions, and temperatures. Figure 3 presents the temporal progression of fire spread for a specific case, demonstrating that the model produces coherent and continuous fire dynamics over time. Figure 4 further illustrates fire behaviour under varying wind speeds and wind directions, showing that the generated fire spread patterns align with the corresponding wind directions, while the extent of fire spread remains consistent with the wind speeds.

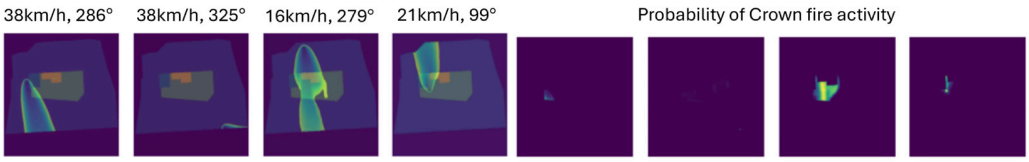


Figure 2. Fire spread (**Left**) and crowning activity (**Right**) with controlled ignition and weather conditions.

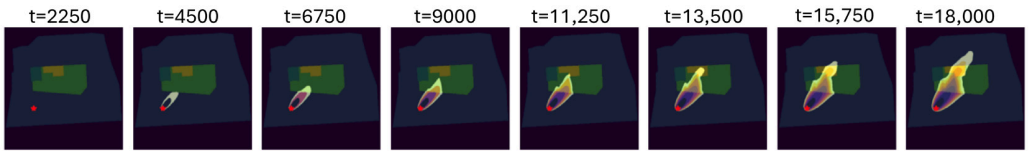


Figure 3. Fire spread on the pine plantation scenario in iFire 2.0 (ws: 15 m/s, θ: 50°, T: 20 °C).

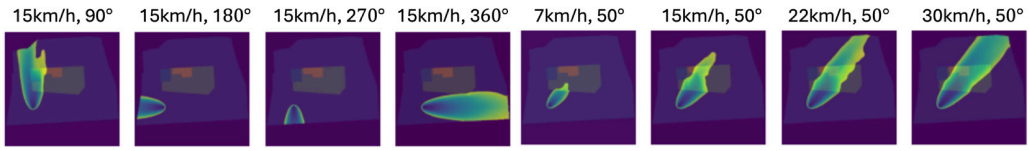


Figure 4. Fire spread under controlled wind directions (**left**) and speeds (**right**).

Finally, Figure 5 presents the fire spread in the 3D visualisation in iFire 2.0, which can be viewed from different angles. It shows that the generated wildfire scenarios are successfully deployed in our immersive visualisation system, providing important materials for wildfire scenario reconstruction.



Figure 5. Fire spread in the Fire 3D model.

6. Limitation

Although the integration of real-world wildfire datasets is planned, the current stage of the project is constrained by the limited availability of high-quality observational fire data. As a result, the present dataset is generated primarily from SPARK simulations rather than recorded wildfire events. Consequently, the learned model reflects the assumptions and behavioural characteristics embedded within the underlying simulator and does not yet fully capture the complexity and variability of real-world wildfire dynamics. Validation and refinement using observational wildfire datasets remain important directions for future work.

7. Conclusions

This paper introduces our DL-based fire behaviour modelling being developed in iCinema's iFire 2.0. The model integrates fuel, ignition, and weather conditions to simulate fire spread dynamics and crown fire activity. A hypothetical pine plantation scenario case study demonstrates that the model successfully learns extreme wildfire behaviours from the given dataset. It builds the foundation for further development using real-world wildfire cases as the next stage of the project.

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