Route Planning in Wildfire Areas by Integrating a Modified A* Algorithm with Deep Learning

Manavjit Singh Dhindsa
Department of Electrical and Computer Engineering
University of Waterloo, Waterloo, Canada
e-mail: ms2dhind@uwaterloo.ca

Kshirasagar Naik, Pin-Han Ho
Department of Electrical and Computer Engineering
University of Waterloo, Waterloo, Canada
e-mail: {snaik | p4ho}@uwaterloo.ca

Marzia Zaman
Research and Development
Cistel Technology, Ottawa, Canada
e-mail: marzia@cistel.com

Chung-Horng Lung
Department of Systems and Computer Engineering
Carleton University, Ottawa, Canada
e-mail: chlung@sce.carleton.ca

Srinivas Sampalli
Department of Computer Scienceg
Dalhousie University, Halifax, Canada
e-mail: srini@cs.dal.ca

***Abstract*—Wildfires pose a significant threat to life, property, and ecosystems, with their frequency and intensity escalating due to climate change. Effective evacuation planning is critical to mitigating wildfire impacts, yet it remains a challenging task in dynamic, high-risk scenarios. This paper presents a framework for safe path planning that integrates wildfire spread predictions from state-of-the-art deep learning models with an optimized A* (OA*) algorithm. The proposed approach utilizes binary fire masks to generate safe and efficient evacuation routes while adhering to strict safety constraints, such as maintaining buffer zones around fire-affected regions. Experimental results show the algorithm's capability to generate actionable paths and accurately identify no-path scenarios under diverse wildfire conditions. This framework offers a robust solution for real-time evacuation planning, contributing to the broader efforts of wildfire management and disaster mitigation.**

Keywords-Route Navigation; Deep Learning; Forest fire; A* Algorithm; Path Planning; Wildfire Prediction; Machine Learning.

I. Introduction

Wildfires, once a natural mechanism for maintaining ecological balance, have transformed into a global environmental and socio-economic crisis. Historically, fires served essential ecological roles, such as clearing dead vegetation and recycling nutrients. However, in recent decades, climate change, combined with evolving fire management policies, has led to a marked increase in both the frequency and intensity of wildfires. Projections suggest that the annual occurrence of very large fires (greater than 5000 hectares) could quadruple between 2041 and 2070 compared to the period from 1971 to 2000 [1]. For example, the 2020 wildfire season in the United States burned over 4 million hectares, including the devastating August Complex fire, which consumed more than 400,000 hectares [2]. These fires caused approximately $19 billion in economic losses and emitted 112 million metric tons of carbon, surpassing the annual emissions of all vehicles in California combined [3].

The repercussions of wildfires extend far beyond the immediate destruction of ecosystems. They threaten biodiversity, water resources, carbon storage, and air quality, while also imposing significant burdens on public health and the economy. Infrastructure losses, increased insurance costs, and healthcare challenges due to smoke exposure are just a few examples of their cascading effects [4], [5].

Given these challenges, there is an urgent need for effective wildfire management strategies, particularly in emergency response scenarios. One crucial component of this is the ability to generate safe evacuation routes based on accurate wildfire spread predictions. Predictive models provide critical insights into the spatial and temporal dynamics of wildfire behavior, enabling the identification of high-risk areas. However, translating these predictions into actionable evacuation plans requires robust path-planning algorithms that can navigate dynamic and hazardous environments.

This paper focuses on the development of a safe path planning framework that utilizes wildfire spread predictions to identify secure evacuation routes. Using results from deep learning models, such as U-Net and Vision Transformers (ViT), which generate binary fire masks representing fire-affected zones, this framework leverages a modified A* pathfinding algorithm to compute safe paths in real time. The proposed approach integrates the outputs of these prediction models into a graph-based search process, ensuring that routes avoid hazardous areas while adhering to safety constraints.

By addressing the challenge of converting wildfire predictions into actionable safe paths, this work contributes to the broader goal of improving emergency response capabilities. The framework demonstrates the potential to support timely and efficient evacuation planning, ensuring the safety of individuals and minimizing the impacts of wildfires on affected communities.

The remainder of this paper is organized as follows: Section II reviews related work on wildfire prediction and pathfinding techniques. Section III describes the methodology, focusing on the use of prediction results from Deep Learning models integrated with a modified A* algorithm for safe pathfinding. Section IV presents the experimental setup, results, and evaluation. Section V concludes with key findings and future research directions.

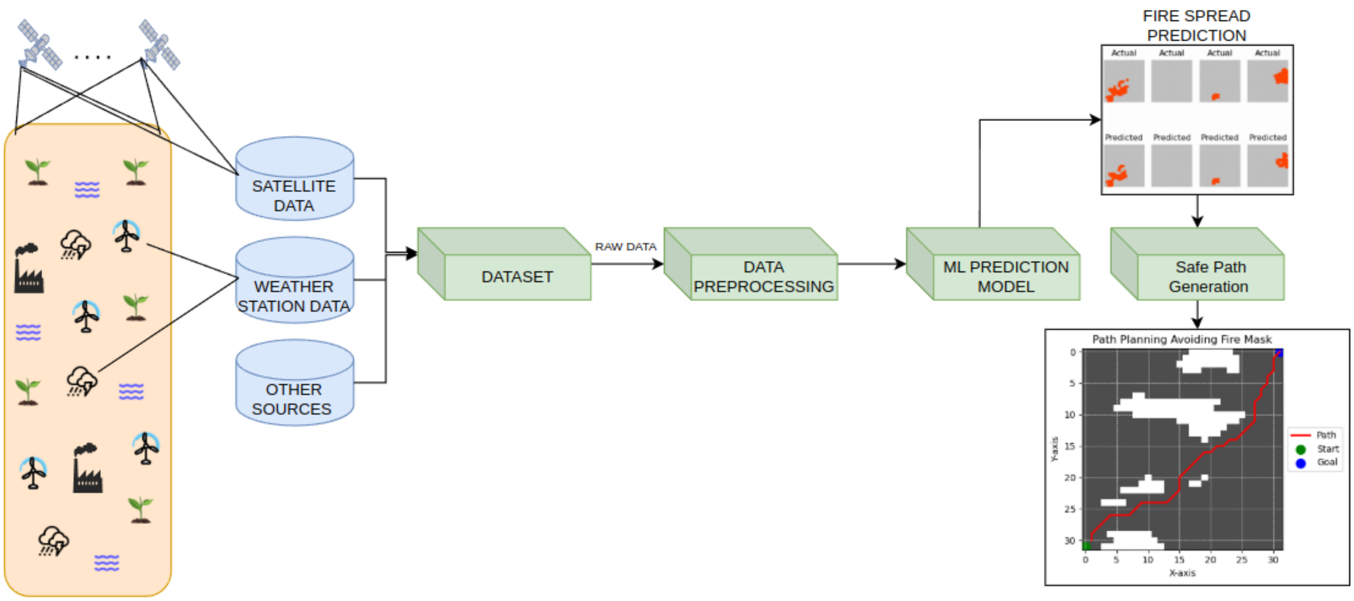

Figure 1: System Model

II. Related Work

Traditionally, wildfire prediction models have been based on empirical, physics-based, and cellular automata methods. Empirical models, like the Rothermel fire spread model, used historical fire data to predict fire intensity and rate of spread [6]. Physics-based models, such as BEHAVE [7] and FARSITE [8], simulate fire behavior by incorporating physical processes, like wind, temperature, and fuel type. Cellular automata models further enhanced fire dynamics simulation by introducing stochastic and spatially explicit models, such as those by Karafyllidis and Thanailakis [9]. While these traditional models were effective, they struggled with the complexity of fire spread dynamics, particularly in non-linear environments. The advent of machine learning (ML) and deep learning (DL) introduced new capabilities. ML models, including Random Forest and Support Vector Machines [10], have demonstrated success in capturing the intricate relationships between various factors influencing fire spread, whereas DL models like CNNs [11] and U-Nets [12] excel in processing satellite imagery and capturing both spatial and temporal patterns. These advancements offer significantly improved predictions by modeling the complex dynamics of wildfire propagation with higher accuracy and robustness than earlier methods.

For deep learning models to effectively predict wildfire spread, robust and multimodal datasets are essential. Datasets like WildfireDB [13] and WildfireSpreadTS [14] combine data from multiple sources, providing essential training foundations despite resolution and data quality challenges. These datasets enable DL models to learn from vast amounts of data, improving the predictive power by accounting for the multifaceted nature of fire behavior. Their ability to integrate spatial, temporal, and environmental data is fundamental in overcoming the limitations of earlier models, enabling better forecasting and resource allocation in wildfire management.

Path planning in dynamic environments, particularly during wildfires, is critical for ensuring the safety of evacuees and first responders. Dijkstra's algorithm, developed in 1959, laid the foundation for finding optimal paths in static environments [15]. However, for dynamic and uncertain environments like wildfires, A* algorithm is more suitable due to its integration of heuristics, which optimize pathfinding while considering obstacles and risk factors [16]. The A* algorithm provides a balance between computational efficiency and path optimality, making it a popular choice for evacuation planning. Moreover, its ability to consider dynamic factors, such as moving hazards or fire progression, allows for real-time adjustments, ensuring timely and safe routes.

For safe evacuation during wildfires, modified versions of path planning algorithms, such as those proposed by Wang et al. [17] and Xu et al. [18], integrate dynamic hazard modeling, risk assessment, and real-time fire prediction data. These modified algorithms adapt to the constantly changing conditions of wildfire environments, ensuring that the generated paths remain safe despite the unpredictability of fire spread. Systems that use real-time fire prediction data, can significantly improve the accuracy of evacuation plans. By continuously updating the predicted spread of the fire, these systems enable the generation of optimal evacuation routes for both the general public and emergency responders, minimizing risks during fire emergencies.

III. Methodology

Wildfires present an unpredictable and highly dynamic threat to life, property, and ecosystems. With accurate predictions of wildfire spread, it becomes possible to plan and execute evacuation strategies. In this work, we focus on the

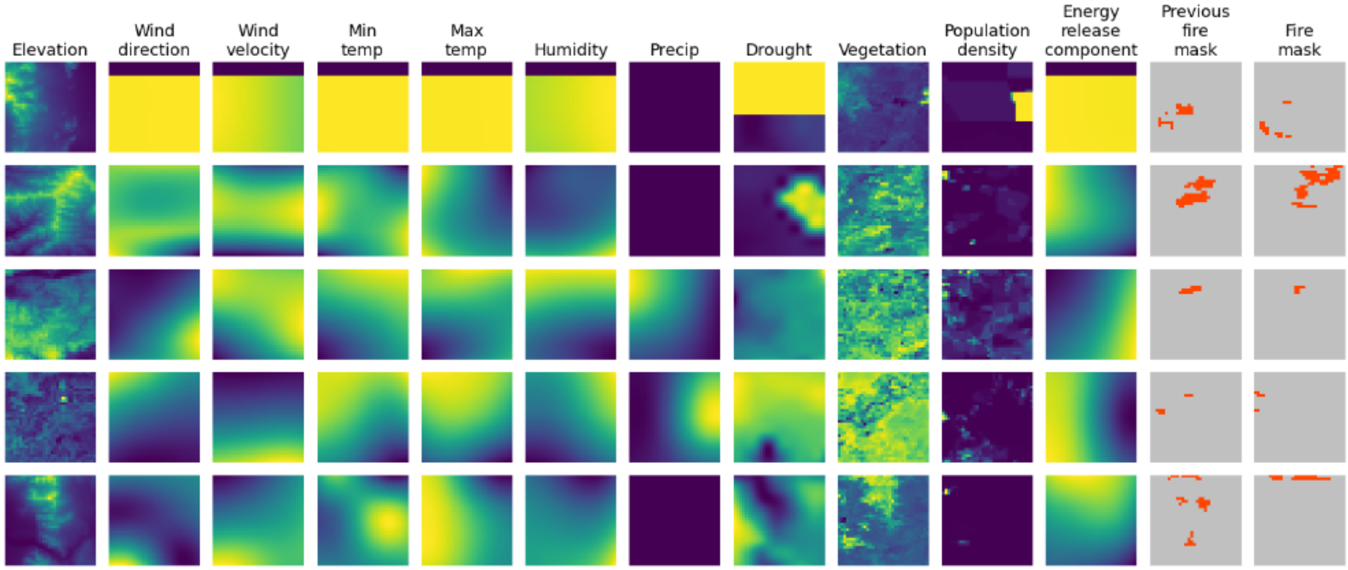

Figure 2: Example images from the dataset showing each of 13 features derived from various sources.

challenge of developing a robust safe path planning framework that integrates results from wildfire spread predictions to generate safe routes for evacuation.

A. Wildfire Spread Prediction

The process of generating a 2D wildfire spread prediction begins by integrating diverse data sources, such as vegetation indices, meteorological data (e.g., temperature, humidity, and wind speed), topographical features, and past fire occurrences. The multimodal inputs are preprocessed to ensure consistency, forming a cohesive dataset for model training (Fig. 2).

The dataset is processed by a deep learning (DL) model in two stages: first, extracting spatial and temporal features to capture relationships like environmental influences on fire propagation; second, identifying complex interactions that traditional methods struggle to model.

The DL model outputs a 2D fire mask prediction for the next day, representing the likelihood of wildfire spread. This binary or probabilistic map indicates fire-affected areas at a grid-cell level. The predicted fire mask can be post-processed for visualization or used directly in downstream applications, such as path planning and resource allocation. This workflow highlights how DL models effectively integrate diverse data to produce actionable insights.

B. Problem Formulation

The prediction of wildfire spread has been achieved using deep learning models such as U-Net and Vision Transformers (ViT). Our task is to leverage these predictions to develop evacuation paths that avoid areas affected by fire. The wildfire predictions are provided as binary grids, where each grid cell indicates whether a particular area is affected by fire or not. The primary challenge is to navigate safely through fire-prone areas using wildfire predictions while ensuring safety and efficiency. This challenge is addressed by formulating the problem as a graph-based search on binary grids

The safe path planning problem involves finding a path from a designated start point (such as the current location of individuals) to a safe destination while avoiding fire-affected areas. Mathematically, we represent the problem as a graph-based search problem, where the grid of wildfire predictions serves as a map. Each grid cell is treated as a node, and the goal is to find a safe route from the start node to the destination node, navigating through non-burning areas.

Let the grid be represented by the binary map $\mathbf{Y} \in \mathbb{R}^{H \times W}$, where H and W are the height and width of the grid, and each element $y_{(h,w)}$ is a binary value: $y_{(h,w)} = 1$ for fire-affected areas and $y_{(h,w)} = 0$ for non-burning areas. The objective is to use a modified A algorithm to find the optimal path, which avoids the cells marked as 1 (fire) and minimizes the distance while maximizing safety.

We define the safe path planning problem as follows:

$$\mathbf{P}_{\text{safe}} = \min_{\mathbf{P}} \left(\sum_{i=1}^{n} d_{i,i+1} \right); \quad y_{(h,w)} = 0, \forall (h,w) \in \mathbf{P} \quad (1)$$

where $\mathbf{P}$ is the path from the start to the destination, $d_{i,i+1}$ is the distance between consecutive nodes along the path, and the condition $y_{(h,w)} = 0$ ensures that all nodes along the path avoid fire-affected areas.

By integrating the results of the wildfire spread predictions into this path-planning process, we aim to provide an automated, safe, and efficient evacuation strategy for areas under threat. The modified A* algorithm, optimized for this context, will use both the fire predictions and traditional route planning criteria (e.g., distance, time, accessibility) to generate the safest and most viable evacuation paths.

The fire predictions are used as input for the optimized A*(OA*) algorithm to implement safe evacuation routes. The fire predictions, represented as binary masks, guide the A* algorithm in finding safe evacuation routes and avoiding fire-affected zones. Fig. 3 illustrates how a complex spiral-shaped fire mask is converted into a binary grid, which acts as a platform for applying the OA* algorithm and generating a corresponding fire mask with pixel values representing "fire" or "no fire." This approach integrates deep learning predictions with pathfinding algorithms to provide actionable, real-time evacuation strategies.

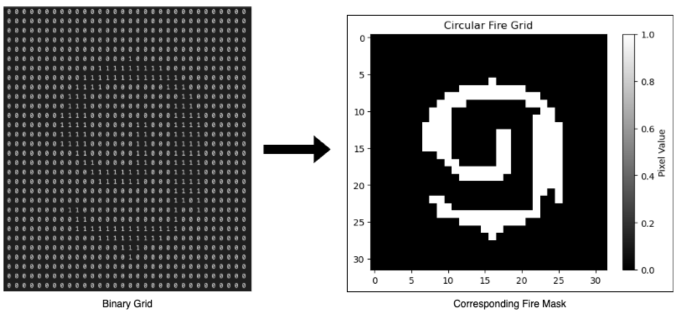

Figure 3: Binary grid converted into corresponding Fire Mask for application of Safe Path Planning.

C. Proposed Algorithm: Optimized A* for Safe Path Planning

The proposed safe path planning algorithm enhances the traditional A* search algorithm to dynamically navigate through wildfire-affected regions, ensuring that the generated paths avoid hazardous fire zones. This modified A* algorithm uses the output of the wildfire spread prediction model, represented as binary fire masks, as input. These fire masks encode areas affected by fire as ‘1’ (danger zones) and safe zones as ‘0’. The objective is to generate the safest, shortest possible path from a start node to a goal node while avoiding fire regions and minimizing risk.

At a high level, the Optimized A* (OA*) algorithm integrates essential components to enable safe path planning. The core components include a heuristic function, a safety evaluation function, and a path reconstruction function. The heuristic function computes the Euclidean distance between nodes, estimating the cost of the shortest path to the goal:

$$f(n) = g(n) + h(n) \tag{2}$$

where $g(n)$ represents the cost from the start node to the current node, and $h(n)$ is the heuristic estimate of the cost to the goal. This function guides the algorithm by prioritizing nodes with the lowest estimated total cost.

The *IsSafe* function evaluates the safety of each node by inspecting its surrounding area within a predefined buffer. For each candidate node, this function iterates over neighboring cells to check whether they fall within fire-affected zones or exceed the grid boundaries. Nodes deemed unsafe are excluded from the search, ensuring the path avoids direct or proximate exposure to fire hazards.

The *ReconstructPath* function traces the final route from the goal node back to the start node. It utilizes a map of predecessors, which records the most efficient path during the search, and iteratively builds the route in reverse, ensuring the shortest and safest path is returned upon successful completion of the algorithm.

The OA* algorithm operates iteratively, beginning with the initialization of the priority queue, which tracks nodes based on their $f(n)$ values. The algorithm starts with the input fire mask, the start and goal nodes, and the specified safety buffer. For each node, the algorithm considers all eight possible movement directions, including diagonals, and evaluates the safety and cost of each neighboring node. If a neighboring node is safe and offers a lower cost than previously recorded, it is added to the open set for further exploration. Unsafe nodes, as determined by the *IsSafe* function, are pruned from the search space.

When a neighboring node satisfies the safety and cost criteria, its $g(n)$ value is updated to reflect the traversal cost, and its $f(n)$ value is recomputed. If the goal node is reached, the algorithm terminates, and the *ReconstructPath* function maps out the shortest, safest route. If the priority queue is exhausted without finding a path, the algorithm concludes that no viable route exists, ensuring that no unsafe recommendations are made.

This integration of heuristic evaluation, safety constraints, and efficient path reconstruction ensures that the OA* algorithm generates paths that are both optimal in terms of distance and safe for traversal. The approach is particularly effective in scenarios requiring real-time decision-making, such as emergency evacuations, firefighting operations, and autonomous navigation in fire-affected regions. By prioritizing safety while maintaining efficiency, the OA* algorithm addresses the critical challenges posed by dynamic and hazardous environments.

IV. EXPERIMENTS & RESULTS

This section presents the results of the safe path planning using the optimized A* (OA*) algorithm, which integrates wildfire spread predictions from a Deep Learning model. The algorithm leverages binary fire masks to find safe evacuation routes while adhering to safety constraints, such as maintaining a buffer zone from fire-affected areas.

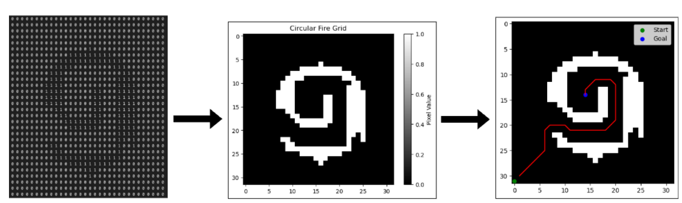

Figure 4: Application of OA* Algorithm on the Wildfire Spread Prediction results.

Fig. 4 builds upon Fig. 3, illustrating the application and outcome of the OA* algorithm on an input binary grid. The fire masks, generated from spread prediction outputs, are

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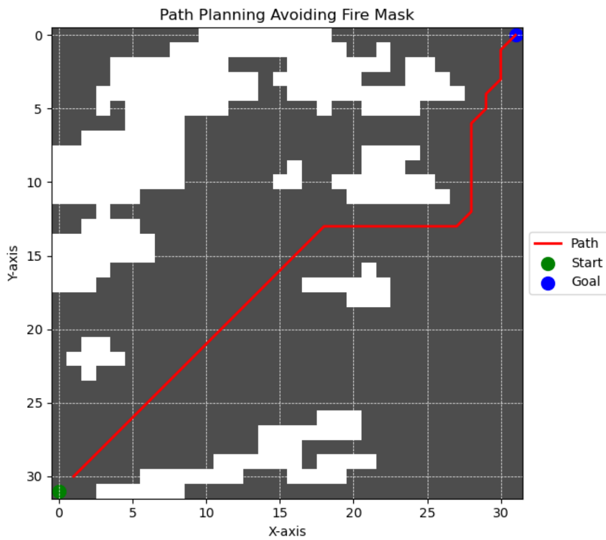
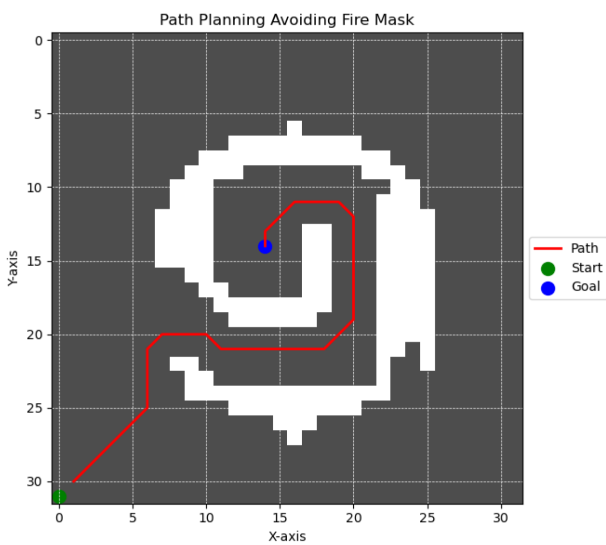
transformed into a binary grid to enable processing by the OA* algorithm. For clarity, these grids are further represented as fire maps. The final result depicts a red line, indicating the safe path between the start (green marker) and goal (blue marker), while adhering to all safety constraints.

A. *Scenarios with Navigable Safe Routes*



(a) Path generated in denser fire areas

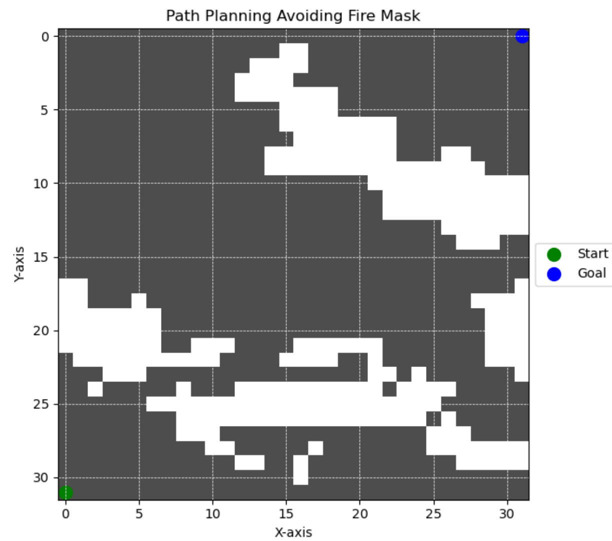


(b) Path generated in complex fire zones

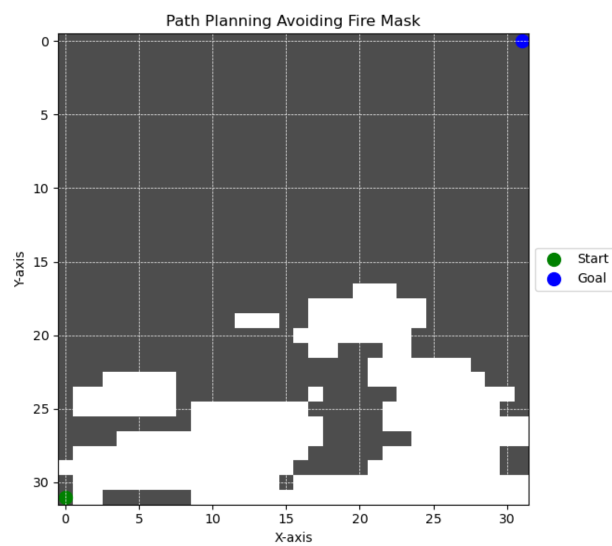
Figure 5: Results of Navigable Path Based on Optimized A* Algorithm

The application of the OA* algorithm on wildfire spread predictions is demonstrated in Fig. 5, showing successful pathfinding from start to goal nodes, avoiding fire-affected regions. In these scenarios, the algorithm navigates a sparse region, selecting a direct route while respecting the safe buffer. Fig. 5a shows the algorithm can handle a denser fire area with narrow corridors, still ensuring safety by avoiding fire zones. The algorithm is equipped to find a longer, safer path around the fire in a large fire-affected area. Fig. 5b represents a complex spiral-shaped fire zone that is navigated successfully, demonstrating the algorithm's robustness.

The results demonstrate the OA* algorithm's ability to effectively utilize fire predictions to provide safe and efficient evacuation routes and validate that the OA* algorithm effectively balances safety and route efficiency. The implemented safety buffer ensures that the generated paths not only minimize distance but also maintain a safe distance from fire zones. The adaptability of the algorithm is evident, as it can navigate from sparse to highly complex fire scenarios without compromising safety.



(a) Absence of safe distance from source to destination



(b) Fire region overlaps or is too close to source/destination node.

Figure 6: Results of No Path Exist Based on Optimized A* Algorithm

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B. Scenarios with No Safe Routes

In some cases, the OA* algorithm was unable to generate paths due to environmental constraints, as shown in Fig. 6. These scenarios highlight the algorithm's accuracy in recognizing situations where no safe route exists. Fig. 6a shows complete blockage of safe passages by fire zones and safety buffers resulting in no path being generated. Fig. 6b Fire regions overlap or are too close to the start or goal nodes, preventing any feasible path from being identified.

These results validate the robustness and reliability of the Optimized A* (OA*) algorithm in leveraging wildfire spread predictions for safe path planning. The algorithm consistently adheres to safety constraints, ensuring that only paths meeting safety standards are proposed while avoiding unsafe recommendations. Its ability to successfully navigate diverse fire scenarios demonstrates adaptability and effectiveness in providing safe evacuation routes. Simultaneously, the algorithm's precise recognition of no-path scenarios underscores its critical role in upholding safety protocols, making it a valuable tool for real-world applications like evacuation planning.

These outcomes validate the utility of the OA* algorithm as a practical tool for emergency planning and real-time decision-making, offering a promising solution for mitigating wildfire risks and enhancing evacuation strategies.

V. Conclusion & Future Work

In this work, we presented an Optimized A* (OA*) algorithm for safe path planning, leveraging wildfire spread predictions generated from deep learning models. The methodology integrates binary fire masks with a graph-based search algorithm to navigate through complex wildfire scenarios, ensuring safety while maintaining route efficiency. Experimental results demonstrate the algorithm's adaptability to varying fire patterns, from sparse to highly dense zones, and its ability to identify no-path scenarios when no safe evacuation route exists. This approach highlights the potential of integrating deep learning predictions with traditional search algorithms to address real-world challenges like emergency evacuation planning.

While the OA* algorithm has proven effective in ensuring safety and efficiency, future work can further enhance its capabilities. First, the quality of path planning outcomes is directly influenced by the accuracy and precision of wildfire spread predictions. Advances in deep learning techniques and the use of higher-resolution, more precisely delineated predictions can significantly improve the algorithm's performance. Additionally, incorporating dynamic updates to account for real-time changes in fire behavior and environmental conditions would enhance the adaptability of the system. Exploring alternative heuristic functions and multi-objective optimization techniques could also offer further improvements, allowing the algorithm to balance safety, travel time, and resource allocation more effectively.

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