Machine Learning informed Cellular Automata for Forest Fire Modeling

Checkpoint 1

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Abstract

Forest fires are a significant concern due to their impact on ecosystems, human life, and property. Accurate prediction of their spread is crucial for effective forest management and firefighting operations. In this project, we propose a novel Machine Learning (ML)-informed hexagonal Cellular Automata (CA) model for simulating and predicting forest fire spread. Our goal is to improve the accuracy and efficiency of forest fire spread predictions by incorporating local spatio-temporal forest data and leveraging the unique advantages of hexagonal cells.

The proposed model integrates supervised ML models trained on historical forest fire data with a hexagonal CA framework. This combination allows the model to capture complex patterns and relationships between factors influencing fire spread, such as vegetation type, wind speed and direction, relative humidity, and temperature. Hexagonal cells offer benefits over traditional square cells, including more uniform neighbor distances, improved packing efficiency, and better symmetry, resulting in a more accurate representation of the forest fire spread phenomenon.

The development of the ML-informed hexagonal CA model involves several stages, including data collection and preprocessing, training and evaluation of supervised ML models, and implementation and testing of the hexagonal CA framework. The model's performance will be assessed using historical forest fire data and compared to existing modeling techniques to demonstrate its potential advantages in terms of accuracy, efficiency, and real-time prediction capabilities.

Description of the system being studied

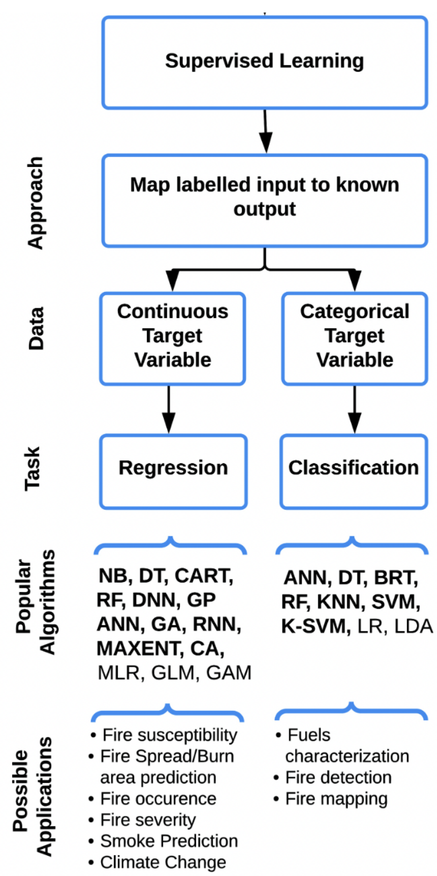
The system being studied in this project is the complex and dynamic phenomenon of forest fire spread. Forest fires are influenced by a multitude of factors, including fuel availability, weather conditions, and topography, which interact in intricate ways to determine the fire's behavior and rate of spread. Accurate prediction and simulation of forest fire spread are essential for effective resource allocation, decision-making, and firefighting operations, as well as for forest management and the protection of ecosystems, human life, and property.

Our focus is on developing a novel ML-informed hexagonal CA model to represent and simulate forest fire spread more accurately and efficiently than traditional models. The hexagonal CA grid divides the forest into interconnected hexagonal cells, with each cell representing a specific section of the forest, including its vegetation type, topography, and other relevant features. The grid's size and resolution can be adjusted based on the specific forest fire scenario being studied. The interconnected nature of the cells allows for the exchange of information between neighboring cells, which plays a crucial role in simulating the spread of the fire.

The model incorporates supervised ML techniques trained on historical forest fire data to derive dynamic rules governing the spread of the fire. These rules take into account local spatio-temporal forest data, such as vegetation type, wind speed and direction, relative humidity, and temperature, allowing the model to capture complex patterns and relationships between factors influencing fire spread. By integrating these ML-derived dynamic rules into the hexagonal CA model, it can better predict and simulate the spread of forest fires under various conditions and scenarios.

Conceptual model

A conceptual model of the system serves as a simplified representation of the complex forest fire spread phenomenon, capturing the essential elements and interactions between the components. The proposed ML-informed hexagonal CA model consists of the following key components:



State Variables: Each hexagonal cell has a set of state variables that represent its current status and properties. Some key state variables include fuel load, moisture content, fire intensity, and vegetation type. These variables are updated at each time step based on the dynamic rules informed by the ML models. These variables are subject to change as we make progress.

Dynamic Rules: The dynamic rules govern the behavior of the hexagonal CA model, determining the spread of the fire and the update of state variables for each cell. These rules are informed by supervised ML models trained on local spatio-temporal forest data, allowing the CA model to capture complex patterns and relationships between factors influencing fire spread. The rules consider factors such as wind speed and direction, relative humidity, temperature, and vegetation type to predict the probability of a cell igniting and the rate at which the fire spreads to neighboring cells. The dynamic nature of these rules enables the model to adapt to changing conditions, providing a more accurate representation of the forest fire spread phenomenon.

Supervised ML Models: The supervised ML models play a vital role in generating the dynamic rules for the hexagonal CA model. These models are trained on historical forest fire data, allowing them to learn the complex relationships between various factors that influence fire spread. By incorporating the knowledge gained from the ML models into the dynamic rules, the hexagonal CA model can better predict the spread of forest fires under various conditions and scenarios. We are currently exploring various models and data source types to achieve this.

Model Initialization and Inputs: To initialize the ML-informed hexagonal CA model, the initial state of each cell in the grid must be set, including the values of the state variables such as fuel load, moisture content, and vegetation type. Additionally, the model requires input data on local weather conditions, such as wind speed and direction, relative humidity, and temperature, which are used to inform the dynamic rules at each time step.

Model Simulation and Outputs: Once initialized, the ML-informed hexagonal CA model will simulate the spread of the forest fire by iteratively updating the state variables of each cell based on the dynamic rules. The simulation will continue until either the fire has been extinguished or a predetermined time limit is reached. The model outputs will include the predicted fire spread, fire intensity, and affected area, which can be used to inform firefighting strategies, resource allocation, and forest management decisions.

Current Work

- Implementation of the stochastic hexagonal grid model.
- Researching methods to use GIS data to train ML models which will inform the probabilities of the stochastic hexagonal CA.

Platforms of development:

- Collaborative editor: Google colab
- Progamming Language: Python
- Libraries used: Numpy, matplotlib

Literature Review [previous submission]
Review of existing literature:

Forest fires are a major natural disaster that can have devastating consequences on both the environment and human life. To understand and predict the spread of forest fires, researchers have developed various models using both Ordinary Differential Equations (ODEs) and Cellular Automata (CA).

ODEs are mathematical models that describe how a system changes over time. In the case of forest fires, ODEs can be used to model the rate of spread of the fire by considering factors such as wind speed, temperature, and the amount of fuel available. A commonly used model for forest fire spread is the Rothermel model [D], which uses ODEs to model the spread of fire based on the fuel properties of the forest, such as fuel load and moisture content. Another model is the Huygens model [E], which combines ODEs and Cellular Automata (CA) to simulate the spread of fire based on factors such as wind speed and direction, slope, and fuel availability.

CA is a computational model that simulates the behavior of a system using a grid of cells, each with a set of rules for how they interact with their neighboring cells. In the context of forest fires, CA can be used to simulate the spread of the fire by dividing the forest into a grid of cells and modeling the spread of fire from one cell to its neighboring cells based on factors such as wind direction, vegetation density, and terrain type [F].

Hexagonal cells have been found to be advantageous in some CA models compared to the more traditional square cells [I]. Here are some reasons why hexagonal cells may be better:

1. Nearest neighbors: In a hexagonal lattice, each cell has six neighbors, as opposed to four in a square lattice. This allows for more natural representations of physical phenomena such as flow, diffusion, and expansion.
2. Symmetry: Hexagons have a high degree of symmetry, which can simplify modeling and make it easier to implement certain rules. For example, it is easier to model rotational symmetry in a hexagonal grid than in a square grid.
3. Packing efficiency: Hexagons are known to be the most efficient shape for packing together in a two-dimensional lattice, which can improve the accuracy and efficiency of the model.
4. Aesthetics: Hexagonal cells can create visually pleasing patterns and shapes, which can be useful in visualizing and communicating the results of the model.

The use of machine learning techniques in modeling forest fire spread has been recently highlighted. Neural networks and support vector machines have been employed to consider more diverse and complex factors such as vegetation type, topography, and climate conditions. The paper [A] discusses the difficulties in developing a tool for simulating the spread of forest fires, which involves estimating fire consequences using a discrete contour propagation model and estimating fire spread using a fuzzy/neural system that takes into account terrain, vegetation, and weather conditions.

Recent strategies involve the use of dynamic network models. [B] presents a modeling approach using dynamic Bayesian networks (DBN) to predict the spread of wildfires in wildland-industrial interfaces, where industrial assets are in close proximity to wildland areas. The model accounts for various factors that affect the fire spread, including weather conditions, fuel types, and industrial assets.

Wildland fire spread modeling using convolutional neural networks (CNNs) is a relatively new approach to predicting the behavior of wildfires. [C] introduces a convolutional neural network (CNN) model for wildfire spread prediction, which is trained on large datasets of wildfire images and incorporates a wide range of input data, including weather conditions, topography, and vegetation type. The model is able to identify patterns and relationships between different factors and generate accurate predictions of fire behavior in real time.

A novel approach of combining a data-driven learning model ELM (Extreme Learning Machine) with CA was introduced by [G] which minimized the dependence of the CA model on the human-made local transition rules. Hexagonal CA models also have been implemented as in [H]. But something that has not been done yet, is the combination of the above two CA models, i.e., ML-informed hexagonal CA model for simulating forest fire spread. This is what we wish to explore in our project.

Progress:
Github link for code: https://github.gatech.edu/mkalicheti3/ForestFireSim
We have replicated a simple forest fire model devised in the paper: https://bib.irb.hr/datoteka/278897.Ljiljana_Bodrozic_ceepus2006_2.pdf. We have introduced more states in the model, namely:

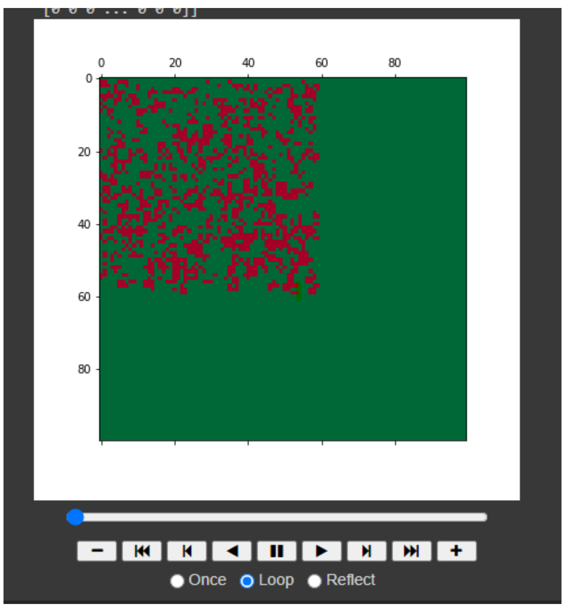
- 0: can be ignited
- 1: fire growing
- 2: burnt
- 3: burning

The initial rules which have been considered for the simulation are as follows::

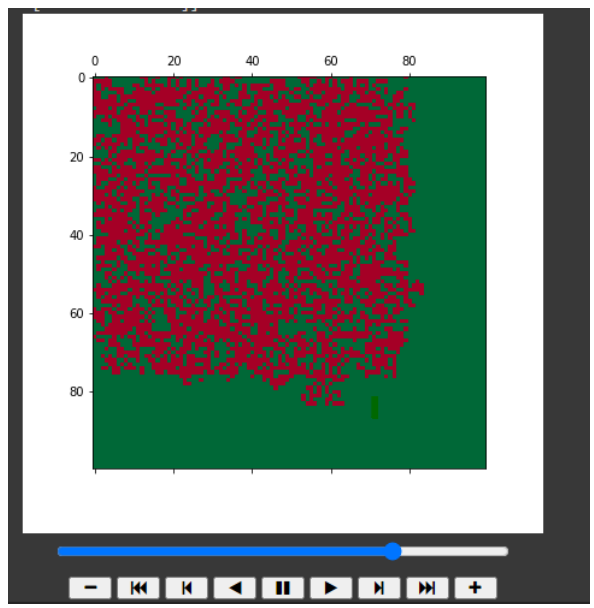
- An ignitable cell remains ignitable unless at least one neighbor is burning (in which case it is burning in the next step)
- A burning cell becomes a burnt cell in the next step.
- A burnt cell becomes a growing cell in the next step.
- A growing cell becomes ignitable in the next step

Results:

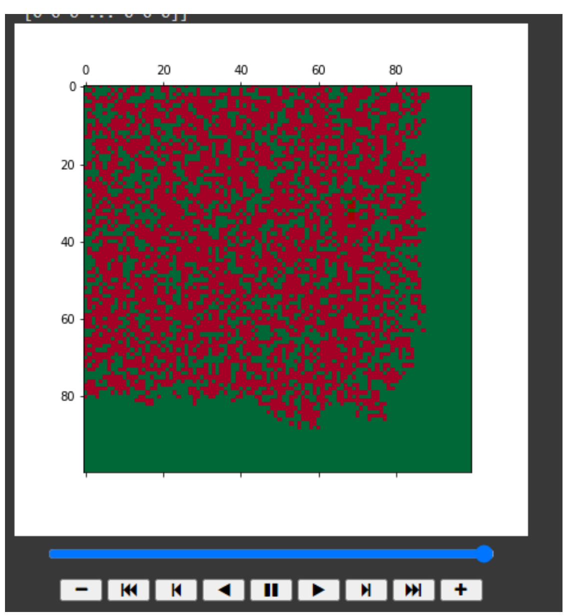
At initial time step:



Intermediate time step:



Final time step:



Division of Labor:

Keerthan, Vishal - Stochastic Hexagonal grid CA model,

Manvitha, Aishwarya - Cellular Automata Model ,

Future division of labor:

Equal distribution: ML model implementation to learn the probabilities, making rules of CA dynamic

References (Literature Review):

[A] https://www.sciencedirect.com/science/article/pii/S0307904X03002117?via%3Dihub
[B] https://www.sciencedirect.com/science/article/pii/S0951832018313887?via%3Dihub
[C] https://link.springer.com/article/10.1007/s10694-019-00846-4#Sec9
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[E] http://fire.org/downloads/farsite/WebHelp/technicalreferences/tech_modeling_fire_growth.htm
[F] https://www.sciencedirect.com/science/article/abs/pii/S0577907320300873
[G] https://www.sciencedirect.com/science/article/abs/pii/S0304380016303064?via%3Dihub
[H]
https://www.researchgate.net/publication/220977472_Predicting_Wildfire_Spreading_Through_a_Hexagonal_Cellular_Automata_Model
[I] https://softologyblog.wordpress.com/2020/06/03/hexagonal-cellular-automata/