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Accident Risk Detection in Urban Trees using Machine Learning and Fuzzy Logic

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Abstract

Knowing the state of trees and their associated risks contribute to the care of the population. Machine Learning, through supervised learning, has demonstrated its effectiveness in various areas of knowledge. The risk of accidents can be predicted by having different tree data, including height, species, condition, presence of pests, the area where it is planted, climatic events, and age. This work proposes a platform to register trees and predict their risk. The solution considers integrating technology and applications for those in charge of maintenance and changes in current procedures. The risk prediction process is carried out through a fuzzification process that contributes to the responsible entities' decision-making. Preliminary results of this research are presented, and the capacity of the developed software architecture is demonstrated, where the scalability of the prediction algorithm stands out.

Keywords: Accident Risk Detection; Fuzzy Logic; Machine Learning; Tree Accident.

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1. Introduction

Chile's municipalities are responsible for the urban tree maintenance and condition review. Falling trees cause damage to buildings, pedestrians, and vehicles, as well as power outages or fires due to damage to power lines [1]. All accidents involve costs for the responsible entities and can cause the death of people [2]. This work proposes developing a system based on Machine Learning to detect potential risks of accidents. This tool will help the responsible entities in the decision-making process by capturing information and analyzing the state of urban trees through several interfaces to avoid an organizational bias [3]. The main functionality is a module to identify the risk presented by an urban tree under various scenarios. This work proposes that an algorithm based on Machine Learning with supervised learning will process tree data and weather conditions to transform them into a qualitative risk value. The system architecture considers technologies such as Python to implement the prediction model and fuzzification of the data. In addition, the solution includes a mobile application developed in Ionic and a backend developed in NodeJs. The following section reviews work about tree risk detection. The third section proposes the prediction system with machine learning and architecture. The fourth section shows the preliminary results of the research.

2. Tree Risks and Accidents

Tree falls prediction is a topic that is still unexplored through machine learning. This work used the terms "tree fall", "accident" and "prediction" in the Web of Science (WOS) and Scopus. We found 12 papers in WOS and 17 in Scopus, but only six papers are related to this work. The tree accident risk detection involves a historical observation of the most common accidents in each location, affecting the road state and the traffic flow [4]. According to [5], many accidents are caused by falling trees due to external factors to the tree. The reported externalities emphasize adverse environmental conditions such as rain or wind before the accidents. Other incident reasons associated with tree falls are tree health problems such as pests and root damage. The literature proposes the implementation of devices to detect risks and the analysis of data to predict accidents. The implementation of devices has been used to create an intelligent network that monitors tree variables such as the inclination to predict potential falls [6]. On the other hand, image recognition and data analysis technologies have been used to detect the road sections with the highest probability of accidents due to trees falling [7]–[9]. All these works rely on historical data with periods of at least one year, which is not feasible in several cases. For this reason, this work proposes risk assessment based on [10] through quantification and characterization of trees and external factors such as proximity to wires. This work aims to link tree fall sensing platforms [6] with guidelines based on previous experience [10].

3. Material and Methods

This work proposes implementing the infrastructure to capture data that characterizes the trees and external risk factors. Table 1 shows the data representing tree characteristics and environmental externalities such as humidity and wind speed. In addition, Table 1 includes a field representing accident risk classified as High, Medium, and Low. High risk means a high probability of affecting the environment and should be treated as soon as possible. Medium risk means the tree may not affect its surroundings, but maintenance is needed in future planning. Low risk means that the tree is unlikely to affect its surroundings and can be safely ignored. Initially, the data of 260 trees with their respective associated risk were obtained through the advice of the local municipality. Subsequently, fuzzy logic transformed the data through a process called fuzzification. Fuzzy logic is closer to human reasoning in front of a specific problem because people usually do not have strictly categorical decisions but a more comprehensive range of options. For example, when a person observes people's height, they might have trouble categorizing height as average or tall because there is no exact range to define a height as average or tall. In this example, the membership functions perform an extra step to human reasoning by defining a precise range of the fuzzy sets.

Table 1 Features Description.

Feature	Data Type	Description
Height	Continuous	Tree height in cm.
Diameter to Chest	Continuous	Trunk diameter at chest height (1.3 m) in cm.
Proximity to Wires	Ordinal qualitative	Tree proximity to Power Lines with the values' far', 'near', 'in contact'. A reference image is saved for the user.
Pest	Binary	Presence of pest in the tree.
Humidity	Continuous	Percentage of relative humidity in the environment.
Type of climate	Ordinal qualitative	Type of weather with the values' thunderstorm', 'drizzle', 'rain', 'snow', 'clear' and 'cloudy'.
Maximum temperature	Continuous	Environment temperature in °C
Wind speed	Continuous	Wind speed in m/s.
Risk	Ordinal qualitative	The risk field is the Risk Rating associated with a tree with High, Medium, and Low values.

Table 2 shows a fuzzy data set, which generates ranges of values for each factor to create a membership function.

Table 2. Fuzzy sets.

Factor	Fuzzy set	Ranges
Height	Low, medium, Tall	[0, 0, 914, 1219]; [914, 1219, 2133, 2438] [2133, 2438, 3048, 3048]
Diameter	Thin, medium, wide	[0, 0, 30, 61] ; [30, 61, 91, 121] ; [91, 121, 182, 182]
Humidity	Humid, little, dry	[0, 0, 30, 35] ; [30, 35, 60, 75] ; [60, 75, 100, 100]
Temperature	Cold, mild, and hot	[-10, -10, 6, 15] ; [6, 15, 27, 33] ; [27, 33, 50, 50]
Wind speed	Calm, slightly strong, strong, strong, very strong	[0, 0, 12, 22] ; [12, 37, 42] ; [37, 46, 49] ; [46, 53, 69, 69]

Table 3 shows the unit of measurement and the membership function per factor, which overlap each class.

Table 3. Units of factor and membership function.

Factor	Unit	Membership Function
Height	Centimeters (cm)	Trapezoidal
Diameter	Centimeters (cm)	Trapezoidal
Humidity	No Apply (%)	Trapezoidal
Temperature	Celsius (°C)	Trapezoidal
Wind speed	Meters/Seconds (mps)	Trapezoidal + Triangular

Once the fuzzy sets are defined, a number related to a qualitative value is assigned to each data, as shown in Table 4.

Table 4 Final Fuzzy Data Set

Data Field	Data Field Name	Description
Height	height	Tall (0), medium (1), low (2)
Diameter to Chest	diameter	wide (0), medium (1), thin (2)
Proximity to Wires	cable proximity	far (0), near (1), contact (2)
Pest	pest	no (0), yes (1)
Humidity	humidity	humid (0), little (1), dry (2)
Type of climate	weather type	thunderstorm (0), drizzle (1), rain (2), snow (3), clear (4), cloudy (5)
Maximum temperature	max_temp	hot (0), mild (1), cold (2)
Wind speed	wind_speed	Very_strong (0), strong (1), mild strong (2), calm (3)
Risk	risk	high (0), medium (1), low (2)

The tree features and the contextual data need several interfaces to provide mobility to users. For this reason, an architecture based on Ionic, Angular, NodeJS, MySql, and Python is proposed. The front-end contains a mobile application and a web application. The backend is based on API Rests to enable the communication between the front-end to the database and the data process engine in Python. These technologies provide a framework for developing mobile applications, web interfaces, and data analytics [11]–[15].

4. Results

This work developed two outcomes, the software development and partial results of the fuzzy model.

4.1. Software Development

Users can enter new trees into the system through the mobile application. The application is developed in Spanish, where each tree considers: Latitude and Longitude, captured with the mobile device's GPS; A circumference, obtained using a measuring tool (tape measure) surrounding the tree trunk, taken at 90 centimeters from the ground; Height: Obtained using a measuring instrument or an estimation based on the distance between foliage and electrical wiring. Users visualize the existing trees on a map, contributing reports and updating the status of the trees already registered in the system. Thus, the system enables the data collection from users about trees, such as the presence of pests, distance from the electrical wiring, and pruning records. In addition, a platform is generated to visualize urban trees for street maintenance tasks. In this platform, the trees can be seen distributed on a map, showing an accident risk prediction for each tree in the next five days.

4.2. Fuzzy Data Model Partial Results

The partial results are composed of 260 training data and 20 test trees. The 260 fuzzy-trees data train the model to predict the new input data risk automatically. Table 6 shows an example of the training data, which contains a risk column to indicate the risk level of trees.

Table 5. Training sub dataset tree example.

height	diameter	cable pro	pest	humidity	weather _type	max _temp	wind _speed	risk
0	2	1	0	2	4	0	0	0
0	0	1	0	2	4	0	1	0
0	2	2	0	2	5	1	1	0

Table 7 shows test data such as location, height, circumference, pests, and cable proximity to check if the fuzzification process predicts the risk.

Table 6. Test dataset of 3 trees

#	height	diameter	Cable proximity	pest	humidity	weather_ type	max temp	wind speed
Tree 1	0	1	2	0	2	4	1	3
Tree 2	1	0	1	0	2	4	0	1
Tree 3	0	0	0	0	0	3	2	3

The fuzzification process allows determining the existing risk associated with each tree. The first three trees have a high risk, while trees 4 and 5 have medium and low risks. It can be deduced that contact with wires and the maximum temperatures influence the risk assessment. Fig. 1 shows the fuzzification of factors, the membership ax indicates the degree of membership, and the factors ax the values. The prediction model achieves an accuracy of 85.4 percent, but it showed problems in the values with membership overlaps.

5. Conclusion

The described application and its functionalities will solve the lack of information on urban trees to avoid accidents. In addition, this work proposes an architecture to predict tree falls based on fuzzy logic, which collects the data from a mobile application and visualizes trees and risk prediction in a web platform.
Finally, it is observed that the system architecture is scalable and extensible to collect new data. The future work will measure the performance of the tree fuzzification process.

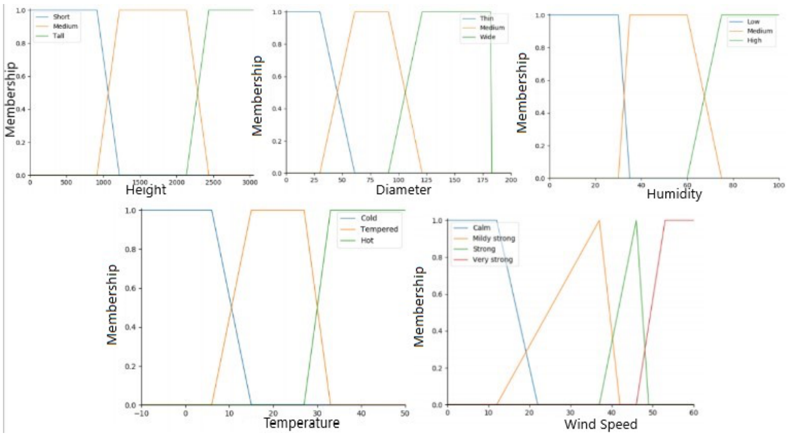

Fig. 1. A Fuzzy feature examples

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