Conference Paper

Peatland Forest Fire Prevention Using Wireless Sensor Network Based on Naïve Bayes Classifier

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Abstract

Recently, peatland forest fires happened massively and gave bad impact for environment. It is necessary to make efforts to reduce of peatland forest fires, Early Warning System (EWS) is one of the solutions. Here, we propose an EWS to prevent forest fire in peatland by using Wireless Sensor Network (WSN). It uses three significant parameters which are oxygen concentration, soil humidity, and environment temperature. Naïve bayes classifier processes the data parameters and then determines forest fire potential. Unusual measurement of the parameters will trigger the classifier decision. Forest fire potential will be displayed through web services. This EWS helps the authorities to monitor and detect forest fire potential in the peatland, so it can be prevented.

Keywords: Peatland Forest Fires, Early Warning System, Wireless Sensor Network, Naive Bayes Classifier, Web Services, Preventive.

1. Introduction

Peatland is the one of wetland that is dominated by organic material that stores 25-30% of the total carbon in the earth. Peatlands occupy more than 7% of the land area in Indonesia (Ferbianti *et. al*, 2018). With this sizeable area, peatlands cannot be separated from human exploitation. Peatlands have been used for agriculture, forestry and mining, especially oil palm (Rieley *et. al*, 1996). In its natural condition, peatlands are always inundated with water. But to meet human needs, peatlands are drained. Drained peatland makes this ecosystem be vulnerable. Twenty years after peatland was used, the threat of fire arose from the drying up of organic matter.

In 2015, huge peatland forest fires occurred in Riau and Jambi, Sumatera. Smoke and pollution problems disrupt public health. Peatland fires also have negative impact to the environment. Peatland fires can release greenhouse gas emissions by 0.81-2.57

Gigatonnes of carbon, equivalent to 40% of world carbon emissions from fuel usage each year (Page *et. al*, 2002). Fires on peatlands are difficult to extinguish because the fire can spread to underground. Preventive efforts become alternative solutions because of the difficulties of blackouts and the high cost of handling fires on peatlands. Early Warning System (EWS) is one of the most important prevention efforts to be applied in monitoring fire risk (Prasastia *et. al*, 2012). Through EWS, locations that have a risk to burn can be predicted. So, it is easy to handle.

EWS can be developed by climate parameters that can trigger fires. In combustion it is known as the term of "fire triangle" where fire will arise if there are three elements that trigger it, there are fuel, heat and oxygen (Countryman, 1975). This study presents the EWS design through the measurement of significant parameters. These parameters are temperatures related to heat; oxygen concentration as a trigger of fire and soil moisture which shows the level of dryness of fuel in the form of organic matter (Pyne *et. al*, 1996). These parameters need the classifier to make the system decide how the factor can make effect on Forest Fire possibility.

Therefore, this research designed EWS to prevent forest fires based on the Naïve Bayes Classifier and use Wireless Sensor Network (WSN) concept. The Naïve Bayes Classifier predicts the forest fire potential in the peatland through the unusual measurements of temperature, oxygen concentration and humidity. Sensor network will make the data acquisition from the environment. The data will be sent to server with IoT concept. The server will compute the data with cloud computing concept and the result will be sent to the end user.

This work will describe about literature review of forest fire prevention with WSN concept in section 2. Section 3 will explain about method used in this paper and describe the analysis about Naïve Bayes Classifier. Section 4 explains about result and discusses about three factor used in this system. Section 5 is the conclusion and the future of work.

2. Literature Review

Currently, many proposals have been implemented with the aim of offering detection and prevention system monitoring for forest fire. Many paper works use wireless sensor network (WSN) in the system of communication and computation to detect the forest fire. Obregon (2009) and Xueli (2010) used system based on wireless sensor network for forest fire prevention. Obregon (2009) used the temperature, humidity, rainfall and wind sensor to make the input of the system and use the Atmega128L for the processor while the sensor network send the data via http communication. On the other hand, Xueli, C. et al. (2009) paid more focus on building the embedded system with the use of TinyOS in the system. Another WSN research, C.-Y. Tsai et al. (2011) proposed the forest fire detection just based on temperature and humidity factors for effectivity to detect fire hotspot.

There is another aspect for the system like WSN routing system and communication model. Zhang, J., et al. (2017) proposed the effective routing system for WSN in forest fire monitoring. The paper compared between routing algorithm LEACH, BEE and BEEM, and chose BEEM for suitable routing algorithm. On the other hand, Wang, W. et al. (2010) made the UWB (ultra wide band topology)for low energy transmission data. Communication model that is mainstreamly used in forest fire prevention is the ZigBee communication. Zhang, J., et al. (2008) use ZigBee as a communication in WSN because of its low-cost and simple communication and Zhu, Y. et al. (2012) combined ZigBee and GPRS communication to connect system to the internet.

Beside communication and network, some paper implemented the algorithm to make early warning system smarter. Toledo-Castro, Josué et. al.(2018) researched the fuzzy logic algorithm for forest fire prevention. The research had some factors like oxygen, carbondioxide, carbonmonoxide, humidity, wind speed and rainfall. Fuzzy algorithm compiled all variables and made the decision of how the potential of forest fire happened

This proposed research offered the early warning system that used wireless sensor network and naïve bayes classifier to detect and decide the potential of forest fire. It has three parameters like oxygen, humidity and temperature. The naïve bayes algorithm will process those variables to the potential of forest fire. The system composed from Wireless Sensor Netwok (WSN), IoT system and application with Graphic User Interface (GUI) in end user.

3. Methods

In order to monitor the forest, wireless sensor nodes and sensors are deployed through forest areas. The system objective is to perform continuous environmental monitoring of forest fire factors such as changing humidity, temperature, and oxygen level variables. The measurement is conducted in every forest area and the gathered information is transmitted to a single board computer (SBC). SBC acts as server which will analyse possible forest fire and display the calculation in Web service. Fig 1 shows the working flow behind purposed forest fire early warning system (EWS).

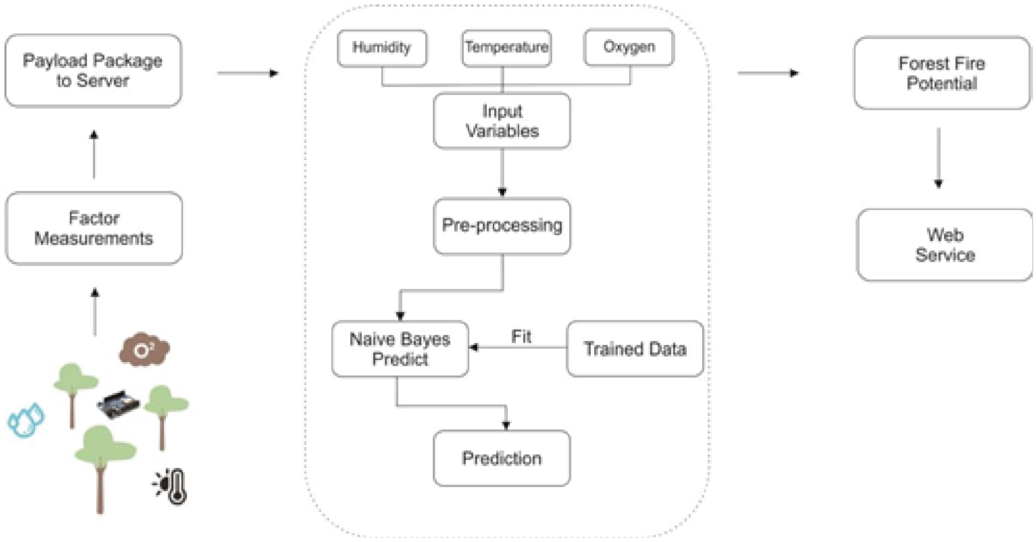

Figure 1: Architecture of Potential Forest Fire Early Warning System.

3.1. Network architecture setup

Wireless sensor networks (WSN) are deployed in specific region by a large number of microsensor node which form to a wireless communication multi-hop network of self-organization (Wang, W. *et al.*, 2010). The group objectives are to sense, collect, and then send the variable information. Purposed EWS uses low-power STARS topology design from another published work (Y. Zhang *et al.*, 2011) as it was durable with forest harsh climate and environment.

For the communication protocol, wireless nodes apply the address for first time uses. This will initialize and calculate shortest route based on time travel and battery. There are specific instructions as follows: wireless sensor channels are monitored after initialized. If the channel is free, the sensor sends a request to assign address, and listens to the channel. Sensors are put to sleep after receiving address from server. Sensors collect data and send after wake-up time. If the sensors do not get the address after certain period of time, it will send a request bit when the channel is free. The communication process is shown in Fig 2.

In order to implement the design above to fit the purposed EWS, there are some minor modifications that were made. First, the nodes that send the complete data payload to server have a fixed address and limitless power from cable to reduce routing time. Second, the server will display the output with a cloud web service. The routing for nodes and server can be looked at Fig 3.

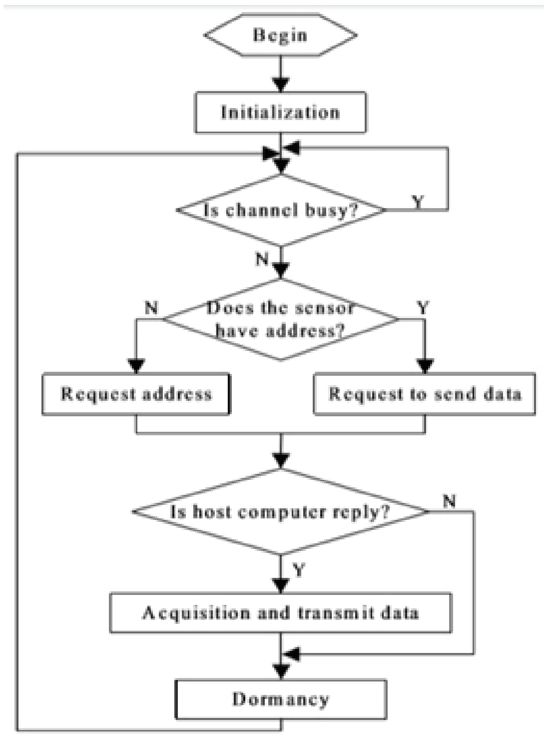

Figure 2: Flowchart of Wireless Sensor Communication (Y. Zhang et al., 2011).

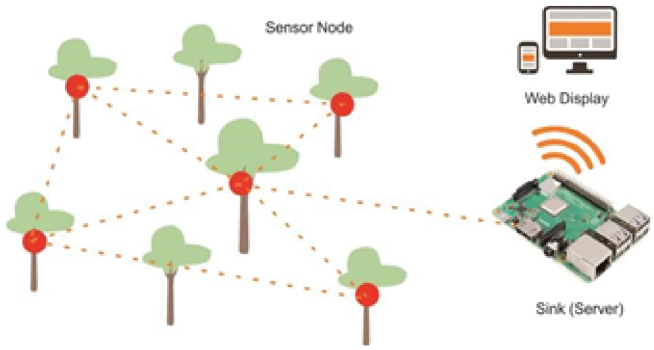

Figure 3: Sensor nodes and server routing for EWS.

3.2. Hardware setup

The Server and sensor nodes have different hardware for certain parts. Hardware architecture of the entire sensor node is mainly composed of sensor boards, signal conditioning circuit, microcontroller, radio module, and power module. For the sink, EWS uses microcomputer that enables low-power operation and computing Naïve Bayes to predict potential forest fire and host web service. Below, Fig 4 shows the sensor node component structure.

Sensor modules consist of integrated temperature with humidity sensor and oxygen level sensor. The node use SHT20, an integrated digital sensor for relative humidity and temperature with an I2C bus made by the Swiss Sensirion Company. This sensor

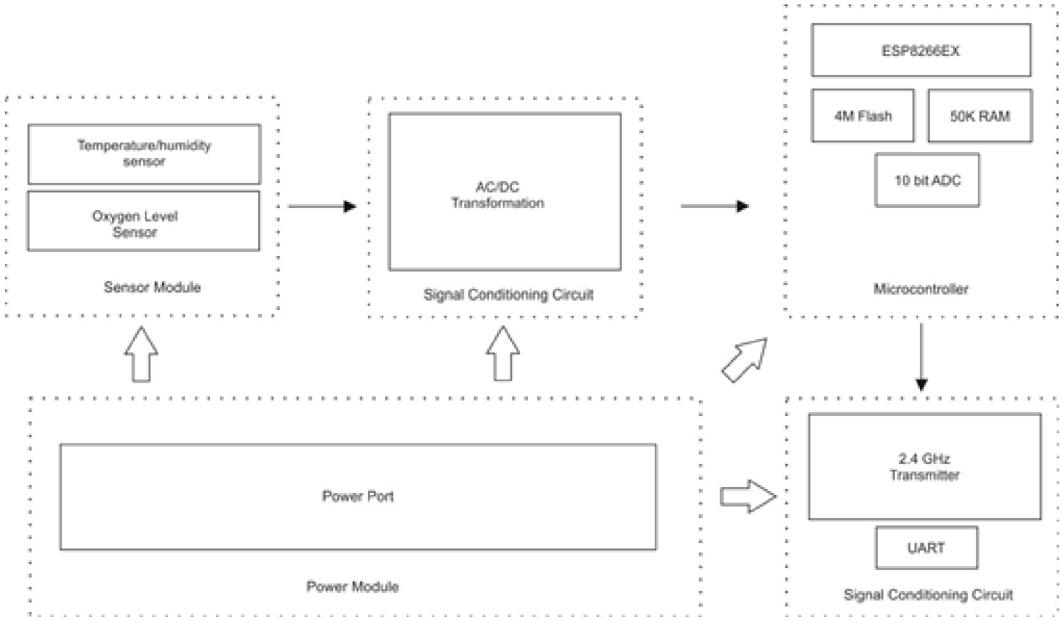

Figure 4: Structure of sensor node.

has some of the most advanced functions such as digital output, ready alignment and calibration-free, has auto-dormancy, and can be completely submerged in water. Its size is extremely small (3 x 3 x 1.1 mm) and requires a supply voltage of 2.1– 3.6 V.

Figure 5: SHT20 sensor.

Xbee Series 1 is a radio communication transceiver and receiver operating with IEEE 802.15.4. A distinguishing feature that makes Xbee the most suitable wireless device for short range telemetry is its very low power consumption. In terms of network topology, a network can be setup based on the star, mesh or cluster tree architecture (J. Li *et. al.*, 2010). With the flexibility in the routing of data, a system can be personalised based on any one of the three architectures depending on system requirements. Although XBee has only 250kbps data rate, it is sufficient for sensing appliances. XBee also comes with 128-bit Advance Encryption Standard (AES) which is a powerful security measure in prevention of data intrusion. Xbee specifications can be overviewed in table 1.

TABLE 1: Technical Specifications of Xbee Series 1.

Standard/Reference	IEEE 802.15.4
Distance (max)	100m nominal
Data rate (max)	250 kbps (2.4 Ghz)
Connection	Ad hoc, Peerto-peer, star
Line of sight	No
Relative power consumption	Very Low
Typical application	Sensing and controlling application
Security	128-bit AES encryption

Figure 6: Xbee Series 1 module.

The Wemos D1 mini pro is a mini wifi internet of Things (IOT) module based on ESP-8266EX microcontroller and provides 4MB flash. The microcontroller can be programmed with Arduino IDE or Nodemcu. It has micro USB for auto programming and it can also be programmed using Over The Air (OTA). One side of the board features ESP8266 module and the other sides have a reset button. It has the ability to use external Antenna and a CP2104 USB to UART IC. The technical specification of this module is shown in below table 2.

TABLE 2: Technical Specifications of Wemos D1 Mini Pro.

Microcontroller	ESP8266EX
Operating Voltage	3.3 V
Digital I/O Pins	11
Analog Input Pins	1
Clock Speed	80 Mhz
Flash	4 M

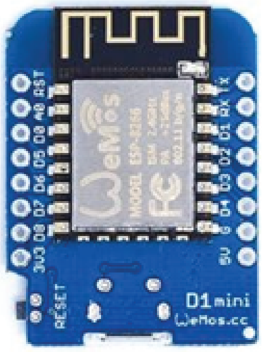

Figure 7: Wemos D1 Mini Pro board.

3.3. Bayesian classification theorem

Bayesian Classifiers are statistical classifiers. Bayesian Classification is based on Bayes Theorem which utilises the conditional probability to classify the data into predetermined classes (Richard O. *et. al.*, 2000). The approach is called “naïve” because it assumes the independence between the various attribute values. Naïve Bayes classification can be viewed as both a descriptive and a predictive type of algorithm. The probabilities are descriptive and are then used to predict the class membership for untrained data. The naïve Bayes approach has several advantages.

It is easy to use. Only one scan of the training data is required. It requires a small amount of training data to estimate the parameters (means and variances of the variables) necessary for classification. In spite of their naive design and apparently over-simplified assumptions, naive bayes classifiers have worked quite well in many complex real world situations. It easily handles mining value by simply omitting that probability in equation 1.

$$P(H \mid X) = \frac{P(X \mid H) \cdot P(H)}{P(X)} \tag{1}$$

Let X be an input data sample whose class label is not known. Let H be any hypothesis, as such that X belongs to a specified class C. For classification we need to determine P(H|X), while the probability that the hypothesis H holds given the input data sample is X. P(H) is the priori probability of H, while the probability that the class labels is C regardless of input data sample. In the same way, P(X|H) is posterior probability of X conditioned on H. P(X) is the prior probability of X. Bayes rule or Bayes theorem provides a way of calculating the posterior probability P(H|X), given P(H), P(X) and P(X|H).

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4. Results and Discussions

This section will explain the result of the system and the discussion in factor analysis and technical analysis.

4.1. Result

In result, it will show about the Graphic User Interface (GUI) of sensor data acquisition and the GUI of Early Warning System. Sensor node will send data to the server and process it to the GUI, so it will make user easy to understand the system. GUI of sensor data is displayed on graphic with Xaxis as time and Y-axis as oxygen, temperature or humidity. The graphic of Peatland Forest Monitoring is shown in Fig. 9. The graphic shows real-time monitoring of peatland forest. This monitoring is being one of the values of EWS (Prasastia et. al, 2012). Data are used for annual record, so user can monitor the behavior of environment data in peatland forest.

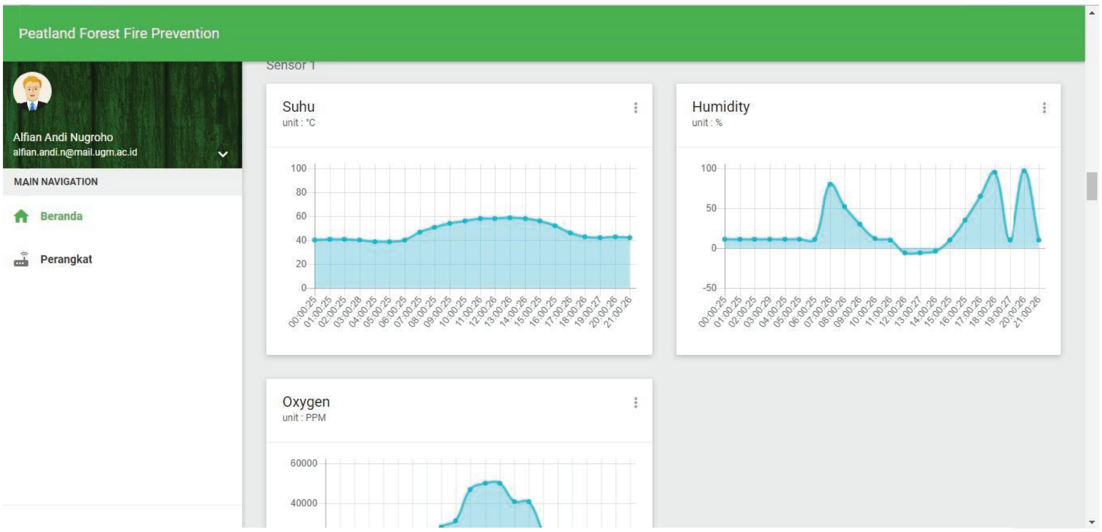

Figure 8: Peatland Forest Data Monitoring.

The early warning system alarm is also built in digital form. Data from environment will be processed with Naïve Bayes Classifier to decide whether the condition is dangerous or not.other than that, Early Warning System also has the information about the value of sensor and the information of node devices. Fig. 10 shows the Early Warning System with alarm of fire potential.

Early warning system will give the information to user about the possibility of forest fire with humidity, temperature and Oxygen factors. If Naïve Bayes Classifier decides the condition is dangerous, or has the possibility of the forest fire to happen , the alarm

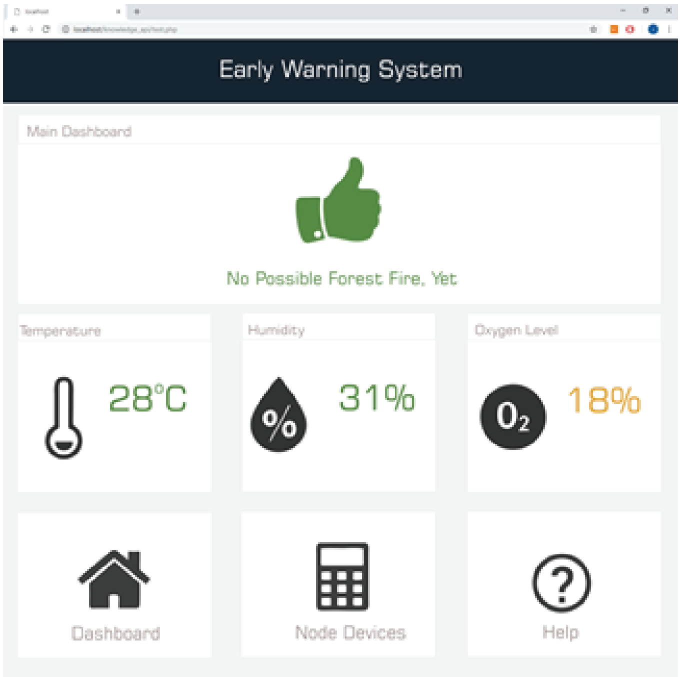

Figure 9: Peatland Forest Data Monitoring.

is red and the logo changes to warning. After that, the system will map how wide the potential of disaster is. Thishappens because sensor value exceeds the threshold and Naïve Bayes Classifier compiles it.

4.2. Discussion of parameter analysis

Peatland is a land formed from a pile of organic matter. Drained peatland makes organic material begin to dry out and easily burn. Organic matter that dries then becomes a potential fuel to trigger fires on peatlands. Fires occur due to the reaction between fuel, heat and oxygen, these elements are commonly known as "fire triangle" (Countryman, 1975). These three elements cannot be separated. To make EWS, significant parameters that can describe the linkages of the fire triangle are needed. These parameters are temperature, soil moisture and oxygen concentration. Temperature accelerates the drying of fuel and can be a heat energy that triggers ignition point (Pyne, 1984). Higher temperature and faster time the fuel dries make peatland be more flammable. During the day, with conditions where temperatures reach 30 - 35 °C it tends to be at risk of burning if it is supported by low levels of organic material moisture and the availability of sufficient oxygen supply (Saharjo, 1999).

Soil moisture is related to the amount of water contained in soil's organic matter on peatlands. Lower level of soil moisture and lower lever of organic material's water content make peatland be more flammable. Low humidity and moisture content in the soil (<30%) makes the combustion process run fast (Saharjo, 1999). Oxygen is a reactant in the combustion process. The amount of oxygen concentration will affect the length of the combustion process. One factor that influences the amount of oxygen is wind speed. Areas with high wind speeds tend to have high oxygen concentrations. Wind also plays a role in accelerating the process of fuel drying (Pyne *et. al*, 1996). The oxygen concentration reaches 21% of the volume of air in the atmosphere. To ignite and maintain the appearance of fire, a minimum of 16% oxygen concentration in the atmosphere is required (Toledo, 2018).

4.3. Discussion of Naïve Bayes classifier

Estimating forest fire risk factors is not an easy task and cannot be executed with complete accuracy. The purposed system uses first pre-process training data by removing bias value with minimum and maximum threshold for each variables. From there Naïve Bayes classifier will take temperature and humidity value as input and address the problem as binary problem (true or false output). Oxygen level will be used to calculate how big the probability of Naïve bayes decision will happen. These methods allow to include the uncertainty of environmental data, the imprecision related to the variation in the parameters and the behaviour of every monitored variables.

4.3.1. Pre-processing

Before the classifier uses the environmental variables as input or training parameters, it needs to be cleared from bias value. Purposed system uses a maximum and minimum threshold to determine which value can be a good indicator of forest fire and at the same time eliminate non-corresponding value that will cause forest fire. The process is shown in Fig. 8 where temperature value is thresholded by minimum value. Each value that doesn't pass will not go to the classifier.

4.3.2. Naïve Bayes binary classifier

Naïve Bayes is used to decide whether forest fire will happen or not. It addresses the problem as binary so it can be trained without many input parameters. From training, the classifier will determine how big each parameter affects probability of the output. For example, 80% of forest fire incidents happen when temperature value is out of

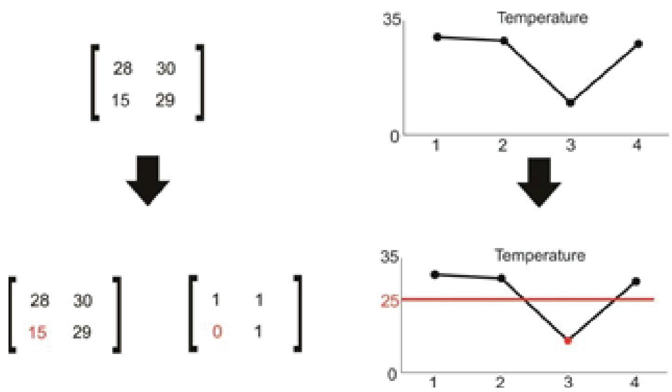

Figure 10: Thresholding process of environmental temperature.

the boundary and 20% is because of low humidity. Then the classifier willmultiply temperature value because it believes temperature value would likely to have bigger effect on triggering forest fire. Processed temperature and humidity variables will be weighted by the full trained classifier. Table 3 shows the example of trained classifier output.

TABLE 3: Trained Naïve Bayes decision from input.

Temperature	Humidity	Output
29	31	No Potential Forest Fire (0)
27	31	No Potential Forest Fire (0)
35	24	Potential Forest Fire (1)
40	32	Potential Forest Fire (1)
30	32	No Potential Forest Fire (0)

4.3.3. Final output

Finally, the oxygen level and rainfall rate are also considered as input linguistic variables .Instead of performing unusual increasing, oxygen level decreases progressively as consequence of being progressively consumed by fire. Hence, this variable may also be catalogued as a useful indicator (Toledo-Castro, Josué *et. al.*, 2018). Fire needs at least 16% of oxygen level to occur, the classifier follows this rule and it affects the final decision of system classifier. System uses rainfall rate value from trusted source https://www.bmkg.go.id/iklim/prakiraan-hujan-bulanan.bmkg. When the classifier outputs possible forest fire, it will also count how large it would be by using equation 2.

$$Luas(Ha) = 5.14 * (DC - 500) - 62.9 \tag{2}$$

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5. Conclusion

The aims of this research are to contribute and solve environmental disaster related to forest fire, prevent it or minimize casualties through early warning system by wireless sensor network (WSN). The system assists to over watch environmental variables contributing to forest fire. It uses robust wireless sensor nodes with low-energy star routing, a web service as user front-end or interface. These elements enable sufficient computation to predict forest fire spreading with low computation time and low energy consumption for transmitting and receiving.

There were still problems that appeared like the system wasn't very accurate because of forest nature anomaly. Accuracy for the forest fire area calculation needs to be improved, as it cannot represent all variations (R2 = 58%). For confidentiality and security, sensor nodes encryption algorithm needs to follow the latest development.

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