Prediction of Underground Fire Behavior in South Sumatra

Using Support Vector Machine with Adversarial Neural Network Support

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Abstract— **Fires, which are the basic cause of smoke haze, can happen due to several reasons, such as the common practice of burning agricultural land, deforestation and delayed rainy seasons (e.g., unusual climatic conditions in the last 20 years, such as El Nino). For plantation companies, land burning is a quick and easy way of preparing land for planting new seeds. Fires that occur in peatlands (peat is a soil composed of partly decaying plant material formed within wetland areas), tend to be under the old soil, generate a great deal of smoke, and are difficult to extinguish. Forest crises and land fires occurring in South Sumatra typically begin in early July, and a fog condition typically lasts until mid-November. According to statistical data, in 2014-2015, 60% of burned land was peatland. In the event of fire, the Government strives to extinguish the fire on peatlands with water bombing, making canals, and others with a variety of local and international aid. However, the most effective way is prevention and/or early intervention. Early intervention is done by installation of aerial and subsurface sensors. Aerial sensors not only detect forest fires in one way, but also detect some additional elements, such as levels of ozone, carbon dioxide, carbon monoxide, and other elements associated with forest fires. Subsurface sensors detect fires below the ground that were previously undetectable. The result of this research is to provide an enhanced baseline analysis for regions of the province of South Sumatra and to determine the probability of fire for particular areas as well as the escalation potential.**

Keywords—forest fire; peatland; smoke; haze; aerial sensor; subsurface sensor.

I. INTRODUCTION

Forest fires have become a world phenomenon. The impacts from these forest fires are very dangerous, not only for the directly affected community, but also for the adjacent environments. As has just happened in Greece in July 2018, it was reported that this wildfire was the worst forest fire in over a decade that occurred in a small resort town near Athens. This tragedy killed at least 74 people, injured almost 200 people, and forced hundreds more to rush on to beaches and into the sea as the blaze devoured houses and cars [1].

Elsewhere in the world, the illegal burning of forests and agricultural land, such as across Indonesia, has blanketed much of Southeast Asia in a dangerous haze, leading to one of the most severe regional (e.g., Association of Southeast Asian Nations or ASEAN) problems in years. The neighbors of Indonesia have complained. For example, Malaysian Prime Minister Najib Razak, has demanded that Indonesia take decisive action again those plantation companies generating the noxious smoke and ensuing haze [2]. The fires, which are the root cause of the haze, stem from a convergence of factors: the prevalent practice of burning agricultural land, deforestation, and a delayed rainy season (due to the most unusual climatic conditions in the past 20 years, such as El Nino). Unfortunately, it is difficult for the plantation companies to stop, for the burning of land is a quick and easy way to prepare soil for new seed. The fires, most of which are burning in peatlands, tend to produce long-lasting, smoky, massive underground blazes. The effects of these blazes are having widespread public health impacts, contributing to respiratory ailments and premature deaths throughout Southeast Asia [3].

In Singapore, news websites post near-hourly updates on the danger of being outside and exposed to the pollution. Some stores in Singapore are providing free masks for children and elderly people. The National Environment Agency in Singapore stated that the haze has entered an “unhealthy range,” and to underscore this point, races for the swimming world cup – the Fédération Internationale de Natation[A] (FINA) (English: International Swimming Federation) Swimming World Cup 2017 in Singapore – were cancelled. A marathon in Malaysia was also cancelled, and all schools were closed as a result of the haze [4].

The South Sumatra forest and land fire crisis of 2015 commenced at the beginning of July. There were some warning symptoms by way of an increase in hotspots; the number of hotspots increased until the haze had spread to areas well outside of South Sumatra. This haze condition lasted until mid-November. Based upon the information provided by the Citra Landsat satellite, forest and land fires affected almost 613 thousand hectares and nearly all the districts and cities within the areas of Musi Banyuasin, Ogan Komering Ilir (OKI), Ogan Ilir, and Banyuasin. The cause of these forest and land fires were principally human-induced, and the ensuing widespread unbridled fires were further fueled by the vastness of the peatland areas. As a statistic, between 2014 and 2015, 60% of these unbridled fires occurred within peatlands [5].

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Due to the severity of forest fires in 2015, the President of Indonesia decided to establish a “presidential office” in the Ogan Komering Ilir (OKI) district, which is a region of South Sumatra. The OKI district had experienced more forest fires than any other region at that time. This “presidential office” served as an Emergency Operations Center for the President to personally conduct emergency fire-fighting operations. The President also created a task force and various governmental posts to serve as a dedicated force for the handling of forest fires. The task force could request water bombing and direct law enforcement to stop the perpetrators of forest fires. To the surrounding communities, the President articulated the impacts of the fires, such as the impact on the health of the people. Examples raised included Acute Respiratory Infection (ARI) [6].

In 2015, the Governor of South Sumatra asserted that there can be no further forest and land fires in the province of South Sumatra. In 2016, the Governor took steps to ensure that there would be a way to contend with these fires. Accordingly, he established a forest and land fire taskforce (Satgas Karhutlah). However, fires continued to occur throughout 2017. In 2017, an extended drought aggravated the situation [7].

In order to avoid similar events, the focus shifted to the effective pathway of forest fire prevention. In this research, sample data from the installation of various aerial sensors and subsurface sensors in particular regions will be utilized, and this data will be processed by various mechanisms, including an analytical engine.

In this study, efforts that have been made by the government in dealing with forest fires will be explained in Section II. The research methodology will be presented in Section III, which consists of data mining and classification. Then, the data processing will be presented in Section IV, which explains how the data is processed using several methods, as well as delineating some types of sensors that can produce more complete and accurate data. Then, the conclusion and follow-up as to what future work will be done are summarized in Section V.

II. GOVERNMENTAL STUDY AS A BASIS

Much research has been done on forest fires in Indonesia, particularly regarding the prevention, as well as root causes of the forest fires themselves. Every year, the province of South Sumatra experiences wildfires; the impacts are classified as mild, moderate, to severe. To better understand these incidents, a governmental study was conducted by the South Sumatra Forest Fire Management Project (SSFFMP), and it examined the causes of forest fires occurring annually in South Sumatra [8].

This research was conducted for 5 years from 2003 to 2007, involving many parties such as the National Government (Ministry of Forestry and Bappenas), and Provincial Governments (Forestry, Planning, and Environment Department), and District/Municipal Governments (Forestry, Planning, and Environment Department). The main objectives of this research were to reduce the level of forest fires and to cope with the impacts of forest and land fires. This included the environmental damage caused by smoke that also affects the territory of Indonesia as well as the territory of neighboring countries. Accordingly, this study was utilized as a launching pad upon which to build this paper. This paper builds upon the study by combining existing sensor data with that of other newly deployed sensors and utilizes Support Vector Machines (SVM) and an Adversarial Neural Network engine (a component of Analytics on Analytics or A2O) support to analyze that data. Our methodology is presented below.

III. METHODOLOGY

A. Data Mining

Data mining is a process of automatically searching for useful information in large data storage [9]. Other terms often used include Knowledge Discovery [mining] in Database (KDD), knowledge extraction, data / pattern analysis, data archeology, data dredging, information harvesting, and business intelligence. Data mining techniques are used to examine large databases as a way to discover new and useful patterns. Data mining is also an integral part of KDD. The entire KDD process for raw data conversion into useful information is shown in Figure 1.

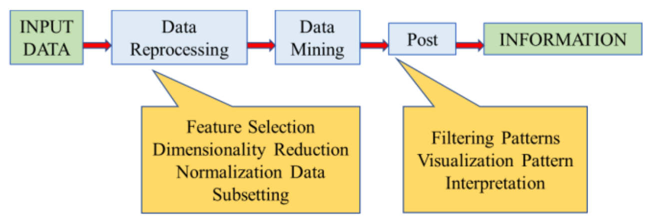

Figure 1. Process in KDD

Input data can be stored in various formats, such as flat files, spreadsheets, or relational tables, and can occupy centralized or distributed data storage in many places. The purpose of pre-processing is to transform raw input data into an appropriate format for further analysis. The steps involved in pre-processing data include combining data from multiple sources, cleansing data to remove noise and duplicate observations, and selecting records and features relevant for data mining jobs. Because there are many ways of collecting and storing data, the prepositional data stages are a time-consuming step in KDD. In addition, the data obtained from the newly deployed sensors constitute prodigious amounts of data, and the resolution desired added to this complexity.

B. Classification

Classification is the method in Data Mining that is most often used to solve real-world problems. This method examines the patterns of historical data (a collection of information - such as features, variables, features - on various characteristics of previously labeled items) with the aim of locating new objects (with previously unknown labels) into groups or classes, respectively.

The two most common steps of classification prediction are the development / training model and the testing /

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deployment model. In the development model phase, a set of input data, including various actual class labels, will be trained. Once a model is "trained," the model is tested against the remaining sample data for accuracy assessment and can ultimately be implemented for real use. In the case of the presented research, the results will be used for the relevant agencies dealing with forest fire prevention. Some of the factors used to assess the model are as follows [9]:

- *Predictive accuracy*, the ability of the model to accurately predict class labels from new or never seen data;
- *Speed*, as pertains to the generation and utilization of the model as well as the computational speed of the system and its constituent components;
- *Robustness (reliability)*, the ability of the model to make predictions fairly accurately, albeit the data may be "noisy" or data may have missing values or be incorrect.
- *Scalability*, the ability to efficiently model predictions with considerable amounts of data;
- *Interpretability*, the level of understanding and insight provided by the model (e.g., how and/or whether the model makes inferences about a particular prediction).

IV. DATA PROCESSING

After obtaining the data from the sensor installation, data processing was performed. Data processing aims to facilitate the data analysis. Data analysis techniques were of two types, namely, (1) descriptive analysis, and (2) inferential analysis. The descriptive analysis of mean, median, mode, and standard deviation was operationalized by using an Access database along with Structured Query Language (SQL) queries. The inferential analysis was based upon linear regression with two or more independent variables (i.e. a statistical method to determine the relationship of a variable with other variables). In this case, the linear regression test was performed using statistical software to ascertain the relationship between the solution of a constraint of particular field with other fields.

A. Inferential Analysis - Regression

Inferential analysis is performed to find the relationship between the variables and then make a determination regarding these variables. The inferential analysis used was linear regression with two or more independent variables, with the calculation analysis performed via statistical software.

The linear regression test of two or more independent variables was used to predict a dependent variable Y based on two or more independent variables (X_1, X_2, and X_3) in a linear equation:

$$Y = a + b_1X_1 + b_2X_2 + b_3X_3 \qquad (1)$$

Where:

Y	= dependent variable
X_1, X_2, X_3	= independent variables
a	= constants
b_1, b_2, b_3	= regression coefficients

In the regression, there are several tests that must be done which are autocorrelation test, collinearity test, coefficient test, hypothesis test, and significance test. The autocorrelation test was performed by the Durbin-Watson (DW) test as follows [10]:

- Positive Autocorrelation Detection:
  If $d < dL$, there is a positive autocorrelation,
  If $d > dU$, there is no positive autocorrelation,
  If $dL < d < dU$, the test is inconclusive or cannot be concluded.
- Negative Autocorrelation Detection:
  If $(4 - d) < dL$, there is a negative autocorrelation,
  If $(4 - d) > dU$, there is no negative autocorrelation,
  If $dL < (4 - d) < dU$, the test is inconclusive or cannot be concluded.

Medium collinearity test is a test that shows whether there is a strong correlation between the independent variables. The method of variable selection on linear regression used the stepwise method. With regards to the stepwise method, for each stage, the independent variable that has the strongest correlation with the dependent variable is included in the model first. It is followed by other variables by testing whether the first variable entered is still maintained in the model. If the first variable probability is still significant in the model, then the variable is applied. If the probability of the first variable is not significant anymore, then the variable is excluded from the analysis. This process stops when there is no longer any independent variable that must be included or excluded from the equation. Furthermore, the regression equation is tested to determine whether the regression equation is valid or not.

B. Support Vector Machine

Support Vector Machine (SVM) uses a linear model to find the best hyperplane as a separator of two classes on a vector input. The best hyperplane can be determined by calculating the hyperplane margin value, which is the distance between hyperplane and the nearest pattern of each class. The pattern closest to the maximum margin of hyperplane is called a support vector. Both classes -1 and +1 and hyperplane dimension d are defined as:

$$\vec{w} \cdot \vec{x} + b = 0 \qquad (2)$$

Pattern $\vec{x_i}$ for negative sample (-1) and positive (+1) can then be formulated:

$$\vec{w} \cdot \vec{x} + b \leq -1 \qquad (3)$$

$$\overrightarrow{w}\cdot\overrightarrow{x}+b\geq+1 \qquad (4)$$

Quadratic programming is used to find the greatest margin value, i.e. $\frac{1}{\|\vec{w}\|}$ by finding the minimal point:

$$\min_{\vec{w}}\tau(w)=\frac{1}{2}\|\vec{w}\|^2 \qquad (5)$$

Using the Lagrange multiplier, the primal form of quadratic programming can be transformed into a dual form with the following equation:

$$L(\vec{w},b,\alpha)=\frac{1}{2}\|\vec{w}\|^2-\sum_{i=1}^{l}\alpha_i(y_i((\vec{x_i}\cdot\vec{w}+b)-1) \qquad (6)$$

Where (i = 1,2, ..., l) and α_i are Lagrange multipliers that are either 0 or positive. The optimal value of the above equation can be calculated by minimizing L against $\vec{w}$ and maximizing L against α_i. Data correlated with a positive α_i is called a support vector.

The SVM concept can be seen in Figure 2, which uses the principle of Structural Risk Minimization (SRM) with the aim of finding the best hyperplane that separates two classes within the input space.

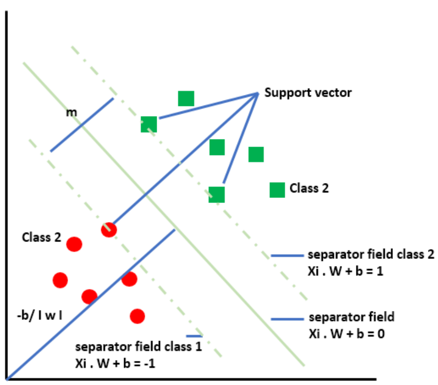

Figure 2. Support Vector Machine Concept

C. *Prediction of Underground Fire Behavior System*

Generally, the prototype system design predicts underground fire behavior by estimating the potential rate of fire explosion, fuel consumption, fire intensity, and fire description. With the help of an elliptical fire growth model, a comprehensive estimate of the fire, via fire perimeter, the growth rate of fire, the behavior of the wing of fire, as well as the rear of the fire. The flowchart is shown in Figure 3.

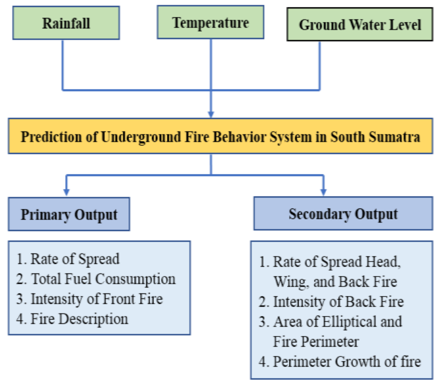

Figure 3. Research Flowchart

The system was modularized into several components, which will be described as follows: Japan International Cooperation Agency (JICA) Sensors, 3D Printed (3DP) sensors, and the the Analytics on Analytics (A2O) system.

a. *JICA Sensors*

The sensors installed by JICA are categorized as a waterlogger or “Automatic Waterlogger Telemetry” sensors with the SESAME II brand, because the main function of this particular sensor is to monitor the condition of the ground water level in the peat area, although in its use, this tool also consisted of several other devices used to collect information/other parameters besides ground water level, namely the level of drought, soil surface, rainfall, and others.

Automatic Waterlogger Telemetry JICA Sensors installed by the Regional Peat Restoration Team consisted of 2 phases. The first phase was carried out in December 2016 with 4 locations, and the second phase was carried out in June 2017 with 6 locations. Once installed, the team started data collection, but the data obtained was not optimal because of problems with telephone lines which have an unstable communication. This phenomenon of unstable communications is not only happening in South Sumatra, but also in other various regions of Indonesia and in other ASEAN countries [11].

Currently, the JICA sensors are deployed, as shown in Figure 4.

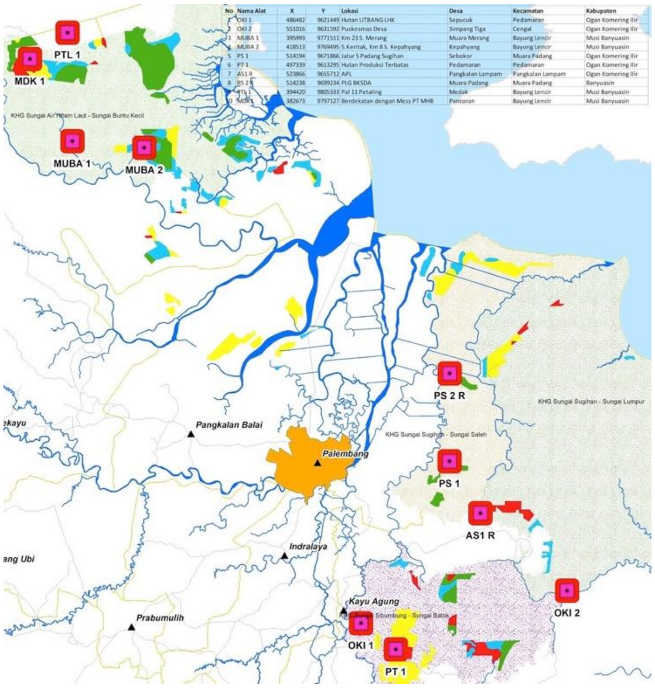

Figure 4. JICA Sensor Deployment [12]

The following locations and coordinates of several sensors are distributed in South Sumatra Province, as shown in Table 1.

TABLE 1. LOCATION AND COORDINATE POINT OF JICA SENSORS IN SOUTH SUMATRA [13]

No.	Code	Location	Coordinate Point
1	OKI-1	- Kelurahan Kedaton, Kecamatan Kayu Agung, Kab. OKI	S3°25'25.82", E104°52' 41.87"
		- KHG Sungai Sibumbung – Sungai Batok	
		- Outside of State Forest	
2	OKI-2	- Desa Simpangtiga, Kecamatan Tulung Selapan, Kab. OKI	S3°19'58.60", E105°27' 33.22"
		- KHG Sungai Sugihan – Sungai Lumpur	
		- Outside of State Forest	
3	MUBA-1	- Desa Bakung, Kecamatan Lalan, Kab. MUBA	S2°2'50.90", E104°3' 4.29"
		- KHG Sungai Air Hitam Laut-Sungai Buntu Kecil	
		- Hutan Produksi KPH Lalan Mangsang Mendis (Production Forest Non Concession)	
4	MUBA-2	- Desa Kepayang, Kecamatan Lalan, Kab. MUBA	S2°5'7.27", E104°16' 2.34"
		- KHG Sungai Air Hitam Laut-Sungai Buntu Kecil	
		- Hutan Produksi KPH Lalan Mangsang Mendis (Production Forest Non Concession)	
5	PS-1	- Desa Baru, Kecamatan Pangkalan Lampam, Kab. OKI	S2°57'49.69", E105°7' 28.19"
		KHG Sungai Sugihan – Sungai Saleh	
		Conservation Forest	
6	PS-2R	- Desa Sidomulyo, Kecamatan Muara Padang,Kab. Banyuasin	S2°43'9.06", E105°7' 45.61"
		KHG Sungai Sugihan – Sungai Saleh	
		Conservation Forest	
7	AS-1R	- Desa Riding, Kecamatan Pangakalan Lampam, Kab. OKI	S3°6'44.24", E105°12' 49.29"
		KHG Sungai Sugihan – Sungai Lumpur	
		Areal Penggunaan Lain (Head of Dusun) (Outside of State Forest	
8	PT-1	- Desa Pulau Geronggang, Kecamatan Pedamaran Timur, Kab. OKI	S3°29'41.87", E104°58' 2.04"
		- KHG Sungai Sibumbung – Sungai Batok	
		- Hutan Produksi Terbatas Pedamaran Kayu Agung, KPH Wil. V Mesuji (Production Forest Non Concession	

In June 2018, the team conducted checks and evaluations of the installed sensors. It turned out that from the ten sensors that had been installed, 2 sensors were lost/stolen. This resulted in a new destination within the data — locations that should be monitored but are not actually monitored. The form of the sensor installed can be seen in Figure 5 below. The sensor features a safety fence to avoid physical interference from the outside but was not always successful against theft.

Figure 5. JICA Sensor Deployment

From the tenth location of the sensor, data was obtained from sensors located in the Village of Cinta Jaya (Department Sepucuk), District Pedamaran, Ogan Komering Ilir and was labelled with the name of the sensor device "OKI 1." The sensor measures the three main components of the temperature, ground water level and rainfall. The collection of sample data is based on the consideration that during July 2018, there were recorded peatland fires involving 105 hectares in the area [14], which were part of the company's land. Data samples can be seen in Table 2, namely as many as 10 samples from the total number of 525 data from each component.

TABLE 2. DATA SAMPLE FROM SENSOR OKI 1 JULY 11th, 2018 – JULY 20th, 2018 [15]

No	Temperature	Rainfall	Groundwater Level
1	30.4	0.0	0.29
2	31.6	0.0	0.31
3	30.6	10.0	0.31
4	29.8	18.0	0.28
5	30.1	0.0	0.30
6	29.4	2.0	0.31
7	28.2	24.5	0.30
8	30.5	0.0	0.28
9	27.9	39.0	0.26
10	29.4	0.0	0.23

Low resolution remote sensing data has been widely used to monitor forest fires such as hotspot detection and burnt land scar mapping. In a study conducted by Indonesian National Institute of Aeronautics and Space (Lembaga Penerbangan dan Antariksa Nasional or LAPAN), the determination of the temperature threshold for hotspot detection was carried out using Landsat-8 TIRS (Thermal Infrared Sensor) data with a spatial resolution of 100 m was utilized so as to increase the accuracy of information with the objective of identifying the source of fire smoke. From these studies, obtained temperature limits that can be said to be potentially a fire are in the range of $\geq 43^{o}$ C [16].

From the existing sample data, temperatures that exceeded the established threshold for those sensors at the Sepucuk area were not detected. At that time, peatland fires were occurring, which required serious and rapid handling by the firefighting team. However, given the sensor specifications, the sensor range was limited to 5-10 km, which was insufficient to reach the area where the fire occurred.

The other weakness of this particular sensor type is that it cannot automatically analyze whether the area has the potential for fire or not. So, the government officers only monitor based upon existing data without being able to ascertain any fire pattern. In the case of underground fires / peatland fires, this sensor cannot be used optimally.

b. 3DP Sensors

The JICA Sensors are spread out throughout the province of South Sumatra, and the parameters collected are sparse. For this reason, 3DP Sensors, such as based upon those that were produced by South Sumatra government officials via the Joint Weather Sensor Team (JWST) for the 2018 Asian Games have great potential. After all, these sensors can collect many parameters, such as shown in Figure 6 and 7 below.

The 3DP Sensors assembled by the JWST are supported by the Center for Research on IoT, Data Science, and Resiliency (CRIDR) team; each sensor contains a cellular SIM card for the required Internet connectivity related to data collection. This avoided the JICA experienced problem of unstable telephones lines.

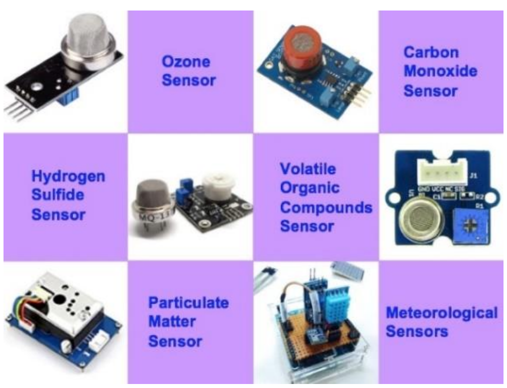

Figure 6. Exemplar Components aboard 3DP Sensors

Figure 7. Exemplar Components aboard 3DP Sensors

c. Analytics on Analytics (A2O) System

Among other modules of the A2O system, there is a Deep Learning module, which is based upon a modified [Deep Convolutional] Generative Adversarial Network (GAN). Each GAN is comprised of two neural networks, which are pitted again each other. This results in the “adversarial” aspect of an unsupervised machine learning paradigm. Unsupervised machine learning refers to the task of inferring a function that describes the structure of “unlabeled” data or data that has not been classified or categorized. The generative aspect is best described by contrasting it to a discriminative aspect. Whereas discriminative models endeavor to learn the boundary between classes (given the labels y and features x, the formulation p(y|x) equates to “the probability of y given x”), generative models endeavor to model the distribution of individual classes (the focus is on “how you get x,” and the formulation p(x|y) equates to “probability of x given y” or the probability of features given a class). GANs are well known for being able to, for example, find the roads on an aerial map, fill in the missing details of an image (up-sampling, given the edges), and construct an image, which postulates how a person might look when they are older. A2O utilizes a stacked GANS; hence the described paradigm is that of Stacked Generative Adversarial Network (SGAN) for the Deep Learning module of A2O.

V. CONCLUSIONS AND FUTURE WORK

The result of this research was to provide an enhanced baseline analysis for regions of the Province of South Sumatra and determine the potentiality of fire for particular areas as well as their escalation potential. This was based upon the requisite characteristics for accelerating fire spread patterns within posited predetermined limits. However, the data from the available JICA sensors was too sparse, and more sensors are needed. Currently, the sparse data does not provide macro-trends or patterns. This is related to the number of constituent components of the JICA sensors and the current resolution of the constituent components. To produce a better assessment, more sensors are needed. As one line of effort, the utilization of 3DP sensors has potential, as they can be scaled in terms of volume (as well as desired add-on components) at very low cost. The combination of both JICA and CRIDR 3DP would likely provide greater context for the analytical engines; A2O’s Deep Learning module was able to glean quite interesting and discerning trends for the locales where the sensors were located, but the few sensors and the far distances among the sensors were problematic.

The location of the sensor installations greatly affected the data generated. Sensor locations play a critical role in many sensor network applications, such as environment monitoring and target tracking. Considering the cyber aspect, simplistic attack vectors, such as Denial of Service (DOS) can render the sensor inoperable. In essence, the location estimation at sensor nodes can be readily subverted and sensor networks can be readily taken off-line. For example, cyber-attackers may provide incorrect location references by replaying the

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beacon packets intercepted in different locations. Moreover, an attacker may compromise a beacon node and distribute malicious location references by spoofing the location or manipulating the beacon signals. In either case, non-beacon nodes will determine their locations incorrectly [17].

Based on the above, the sensors currently in South Sumatra Province have not been able to produce the requisite data so as to be able to determine an accurate pattern of fire distribution. Predictions of forest fires cannot be done precisely because of the many weaknesses pertaining to the quality of components and data, so it cannot be determined whether the monitored areas pose fire potential or not. Sensors of appropriate quantity and quality will greatly assist South Sumatera province as pertains to forest fires.

After this research, it is expected that more high-quality sensors will be installed in South Sumatra and a system that can provide outcall notification to the control room and first responder smartphones will be implemented. This is aimed at preventing and handling forest fires more effectively and efficiently.

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