Vol. 24 No.1 (Januari 2023) 081-088
e-ISSN 2548-6101 p-ISSN 1411-318X

Jurnal Teknologi Lingkungan

Journal Homepage: ejournal.brin.go.id/JTL

Support Vector Machine Analysis for Potential Hotspot Over Papua Island

Support Vector Machine untuk Potensi *Hotspot* pada Pulau Papua

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INFORMASI ARTIKEL

Histori artikel:
Diterima 25 Januari 2022
Disetujui 22 Agustus 2022
Diterbitkan 31 Januari 2023

Kata kunci:
Klasifikasi
Papua
SVM
Kernel polinomial
hotspot

ABSTRAK

Pulau Papua merupakan wilayah yang sering mengalami kebakaran hutan atau lahan dan tercatat mengalami kebakaran luas dari tahun 2013 hingga 2018 mencapai 2.092,44 Ha, sedangkan penelitian yang masih sangat terbatas mengindikasikan kawasan yang mendesak untuk dipantau secara intensif untuk melindungi hutan yang tersisa di Papua. Salah satu indikator terjadinya kebakaran hutan atau lahan dapat diketahui dengan munculnya titik api di atas wilayah daratan. Sebagai upaya penanggulangan kebakaran hutan atau lahan, penelitian ini memanfaatkan data titik api (lintang, bujur, suhu kecerahan, daya pancar api, dan kepercayaan) untuk mengetahui daerah yang memiliki titik api dan mengklasifikasikan data titik api menjadi tiga potensi kebakaran (risiko rendah, risiko sedang, dan risiko tinggi). Penelitian ini berhasil mengimplementasikan metode Support Vector Machine (SVM) untuk mengklasifikasikan data hotspot. Hasil penelitian ini menunjukkan bahwa metode SVM dapat digunakan dalam proses klasifikasi data titik api di Pulau Papua selama tiga tahun (2019, 2020, dan 2021) dengan hasil yang didapat adalah potensi kebakaran. Terdapat 2.214 data hotspot yang termasuk dalam kategori risiko rendah; 15.412 titik api dengan risiko sedang; dan 4.479 titik api dengan potensi risiko tinggi. Selain itu, penelitian ini juga menemukan bahwa jumlah kejadian hotspot tertinggi terjadi pada bulan Agustus dan terendah pada bulan Januari untuk setiap tahun analisis. Penelitian ini memetakan posisi spasial kejadian titik api berdasarkan tingkat risiko di pulau Papua yang menunjukkan bahwa titik api paling banyak terjadi di Papua bagian Selatan (Kota Merauke, Kota Tolikara, dan Kota Puncak Jaya). Terakhir, penelitian ini menghasilkan nilai kebenaran 91,475% untuk teknik pengujian Polynomial Kernel dan 93,667% pada Confusion Matrix sebagai proses validasi.

ARTICLE INFO

Article history:
Received 25 January 2022
Accepted 22 August 2022
Published 31 January 2023

Keywords:
Classification
Papua
SVM
Polynomial Kernel
Hotspot

ABSTRACT

Papua Island is an area that often experiences forest or land fires and is noted to have extensive fires from 2013 to 2018 reaching 2,092.44 Ha, while there is still very limited research indicating the urgent area to be monitored intensively to protect the forest left in this area. One indicator of the occurrence of forest or land fires can be known by the appearance of hotspots over the land area. As an effort to overcome forest or land fires, this study utilizes hotspot data (latitude, longitude, brightness temperature, fire radiative power, and confidence) to find out the area that has a hotspot and classifying hotspot data into three potential fires (low risk, medium risk, and high risk). This study succeeded to implement the Support Vector Machine (SVM) method for classifying hotspot data. The results of this study indicate that the SVM method can be used in the process of classifying hotspot data on Papua Island for three years (2019, 2020, and 2021) with the results obtained are being potential fires. There are 2,214 hotspot data included in the category of low risk; 15,412 hotspots in medium risk; and 4,479 fire hotspots in high-risk potential. Furthermore, this research also found that the highest number of hotspot occurrences was in the month of October and the lowest number was in the month of January for each year of analysis. This research mapped the spatial position of hotspots occurrences based on the rate of risk over Papua island that showed the most occurrences of fire hotspots was in the South part of Papua (Merauke City, Tolikara City, and Puncak Jaya City). Finally, this research produces 91.475% truth values for the Polynomial Kernel testing technique and 93.667% in the Confusion Matrix as a validation process.

1. INTRODUCTION

1.1 Background

Forest or land fires are increasingly affecting national and international attention as environmental and economic issues. Based on Regulation of The Minister of Forestry Number P.12/Menhut-II/2009, forest and land fires are one of the leading environmental problems that cause economic, ecological, and social problems. The island of Papua is an area prone to fire, and it was recorded that the area of forest or land fires from 2013 to 2018 reached 2,092.44 Ha of the total area of Papua Island 786,000 Ha (Forestry, 2015; Tasurruni *et al*., 2019). Forest or land fires often occur due to the use of fire in clearing forests or land because it is considered fast and practical by the community in preparing forests or land function as Industrial Plantation Forests (HTI), plantations, and agriculture (Hendri, 2019; Purnomo *et al*., 2017; Riyanto *et al*., 2020). Forest or land fires can be monitored using remote sensing satellites, which can detect the presence of hotspots on the earth's surface.

The hotspot is an area with a higher temperature than the surrounding area, which is represented in a point with certain coordinates, where the hotspots are an indicator of forest or land fires. The island of Papua is a region that has hotspots. In 2018 there were 4,875 hotspots with a confidence level of more than 50% (Rowe *et al*., 2020; Tasurruni *et al*., 2019). Therefore, in an effort to overcome forest or land fires, it is important to know which areas have hotspots and classifies the hotspots into three predetermined fire potentials low, medium, and high, by utilizing the hotspot data. Hotspot data that will be utilized in the classification process are data on latitude, longitude, brightness, confidence, and fire radiative power. Classification of hotspots can be implemented with the Support Vector Machine (SVM) method (Maione et al., 2016; Mather & Koch, 2011). This method can find the best hyper-plane that functions as a separator of two classes in the input space (Benabdelkader et al., 2007; Fauvel et al., 2012; Feng et al., 2016).

The concept of classification with the SVM method is an attempt to find the best hyperplane that functions as a separator of two data classes in the input space (Benabdelkader et al., 2007; Maione et al., 2016; Mather & Koch, 2011). Patterns that are members of two classes are 1+ and -1, and various dividing lines. The best decision boundary (Hyperplane) between the two classes can be found by measuring the margin of the hyperplane and looking for the maximum point. Margin is the distance between the hyperplane and the closest data from each class. The closest data is called a support vector. In the SVM method, there are linear and non-linear (Kernel tricks). The SVM method is a linear hyperplane that only works on data that can be separated linearly. For non-linear data class distribution, the Kernel approach is usually used in the data set's initial data features (Andris et al., 2013; Ding et al., 2017; Mountrakis et al., 2011).

In the classification of multiclass cases, more than one hyperplane is formed. One method of approach used is One Against One (OAOSVM) (Aburomman & Ibne Reaz, 2017; Cui et al., 2017; Gupta et al., 2012). The "One Against One" strategy, also known as "Pairwise Coupling", "All Pairs", or "Round Robin", consists of building one SVM for each class pair. Thus, for problems with class c, c (c-1) / 2, SVM is trained to distinguish samples from one class from another class of samples. Usually, the classification of unknown patterns is carried out according to the maximum voting, where each SVM votes for one class. Each classification that meets the requirements using the model of the first class is positive and the model of the second class is a negative example. To combine these classifiers can use an algorithm from Max Wins, which finds the next class by selecting the class chosen by the majority of classifiers. The number of models used for each training of OAOSVM classifiers is smaller, while only models from two of all classes are considered. The smaller number of models makes the training time shorter. The SVM combines the linear Kernel function and the RBF with a classification accuracy of 96.6%, while the KNN method results in a classification accuracy of 92.28%, seen from the accuracy results, the classification accuracy with the SVM method has a better performance than KNN. Therefore, the researcher tries to apply the SVM method to the classification of hotspot data because of the high level of accuracy and iteration accuracy for classifying data (Heinzel & Koch, 2012; Rawashdeh et al., 2019). Implementing the SVM algorithm into the data of hotspot occurrences in Papua Island can reveal some interesting knowledge to see the distribution of fire.

1.2 Purpose

This research aims to see the pattern of hotspot fire occurrences over Papua Island with an integrated machine learning algorithm of support vector machine. This algorithm has a better way to understanding the data with the Kernel functionality. Furthermore, this research would classify the hotspot data into three classes based on the priority rate.

2. METHODS

The hotspots are an indicator of the cause of forest fires. Papua Island is one of the regions that has contributed many hotspots, from 2018 to 2021, the number of hotspots reached 22,013 points. The level of fire risk at each hotspot in a region can use data hotspots. The hotspot data has attributes: Latitude, Longitude, Confidence, Brightness Temperature, and Fire Radiative Power. With a description of the problem, there is a system that is able to overcome the above problems so that the hotspots in this area can be classified according to the level of fire risk that has been determined. In this study, this class is low, medium, and high, through system intermediaries, it is expected to inform the level of risk through the system. Figure 1 shows how the processing step in this research was implemented.

This research method explains the system requirements and the steps taken in this research. The input data used are data on hotspots of Papua Island in 2016, 2017, and 2018. The variables used in this study consist of six variables as input = x: Latitude, Longitude, Confidence, Brightness Temperature, and FRP (Fire Radiative Power). While the Output Data needs to consist of 3 classes (Low risk, medium risk, and high risk). The classification process using the SVM analysis method with hotspot data input variables are brightness, confidence, and FRP, and the target variables of potential fire level is low, medium, and high. The completion steps are as follows:

a. Enter hotspot data according to the format in R software.
b. Divide the data into training data and data testing, namely 2018 as training data and 2019-2021 data as testing data.
c. Determine the method of approach to look for the SVM Multiclass hyperplane with the concept of SVM One against One (OAO).
d. Determine the Kernel function that will be used to model the SVM OAO hyperplane.
e. Determine the value of the Kernel parameters that will be used for modelling the SVM OAO hyperplane.
f. Get alpha and b or support vector values.
g. Form three hyperplane equations comparing hotspot data.
h. Make classification predictions.

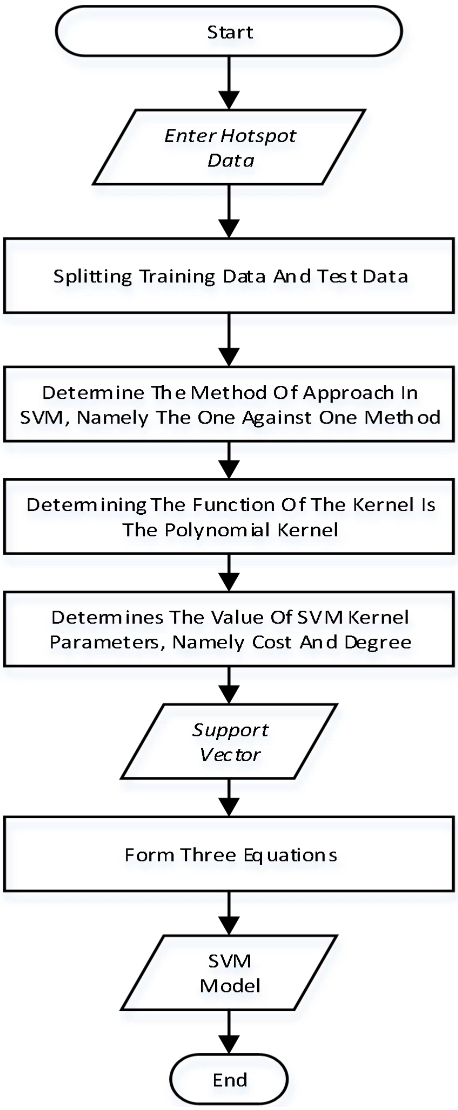

Figure 1. Research flowchart

2.1 Validation Process

The performance evaluation of the classification model was tested using the method of the confusion matrix and K-Fold cross validation to see the performance of classification by calculated the classification accuracy of prediction results and showed the best Kernel parameter and function values. In this study, accuracy testing was used to measure the true value of the results of the classification process on hotspot data using the SVM method, and the accuracy testing method using the Confusion Matrix. The confusion matrix (Ozdarici & Turker, 2007; Tsutsumida & Comber, 2015) or error matrix is a matrix that displays the visualization of the performance of the classification algorithm using data in the matrix. It compares the prediction classification against the actual classification in the form of False Positive (FP), True Positive (TP), False Negative (FN), and True Negative (TN) from the information. Confusion Matrix for a three-class classification system) is described in Table 1.

Table 1. Confusion matrix class

Confusion Matrix		Predicted		
		Class 1	Class 2	Class 3
Actual	Class 1	TP	FN	FN
	Class 2	FP	TN	FN
	Class 3	FP	FP	TN

2.2 System Requirements

This system analysis includes the functionality of the user interface and system workflow. Based on the analysis functionality, this study would develop an application to make the visualization of the algorithm become visible. The application can provide visualization information on the map of the area with a hotspot and fire level risk and classifies hotspot data using the SVM method. It also has to be able to show the visualization menu, the Hotspot data menu, the graph menu, and the classification menu. Figure 1 shows the workflow diagram of the potential fire detection application system based on the classification of hotspot data. One of the functionalities of the user interface is that the user can enter the hotspot data to be classified in the form of a file (.csv) then the system will perform a classification process and display the results of the classification of hotspot data. These results can be seen in the visualization menu as a map with information on regions that have hotspots and potential fires at that point.

The process of classification of hotspot data using the Support Vector Machine (SVM) method is divided into several diagrams, as in Figure 1. Before the prediction process determines the potential for fire, a training process is carried out to obtain the SVM model, which will be used in the classification process, in the training process using input data (X), Confidence, Brightness, and FRP. Training data contained 80% of all data, and 20% will be used for test data. The system will process the separation of hotspot data into training and test data, 2018 data as training data and 2019, 2020, and 2021 data as testing. The process begins with selecting a multiclass SVM hyperplane approach (One Against One method), followed by the process of selecting the Kernel function for hyperplane modelling and selecting the value of Kernel parameters (Cost and Degree).

From the process, the output of support vector data was obtained from Confidence, Brightness, and FRP. These three data are compared and will form three equations that produce the output of the SVM model in the form of class target value data. The result of the training process is the SVM model, which will be used to classify predictions based on new data. The prediction classification process is a process to get predictive results from recent data is the potential for fire. The input data used in the classification prediction process is the SVM model obtained from the training process. A flow diagram of the classification prediction process used a Support Vector Machine (SVM). The classification process starts with inputting the SVM Model and test data, then the data will be in the process where the SVM model is used to introduce classification to the test data so that it can be seen in which class the data is in the stored model, then continued the new data prediction process, in this prediction data will be compared using the approach method, One Against One by comparing the target value data so that the prediction results obtained in the form of potential fire data.

3. RESULTS AND DISCUSSION

3.1 Discussion of Classification with Support Vector Machine (SVM)

In the case of Multiclass SVM One Against One (OAO) (Alita et al., 2020; Feng et al., 2016), the number of equations formed is as many ask or the number of classes. In this study, where the data were classified into three classes, the process forms equations (confidence ~ brightness, confidence ~ FRP, FRP ~ brightness) to see where the data would belong to a certain class. These three equations are then compared using a Polynomial Kernel with parameters C = 500 and d = 1, where C is the number of training and d is the number of dimensions. These parameters are used to map training data using polynomial Kernel functions in Equation 1.

$$K(x,y) = (x,y^T+c)^d \qquad (1)$$

Where for degree-d polynomials, x and y are the vectors in the input space, and $c \geq 0$ is a free parameter trading off the influence of higher-order versus lower-order terms in the polynomial.

After the training data is mapped using the Kernel function, the support vector is obtained with the help of R software. Support vectors are then used in SVM equations to predict the classification of testing data. The result of this mapping is the SVM Model. The SVM model formed is used to predict test data, which still uses the One Against One (OAO) Multiclass approach. Three equations are formed from the target variable (medium/high, medium/low, and high/low). From these three equations, each support vector value in each column of this equation will be compared to get predictions from new data, namely the potential for fire. Figure 2 is a calculation to get the prediction results, where the approach to getting results is to use the SVM OAO method. It is described the sample data that will be searched for the prediction results in Table 2.

Table 2. Predictive data

Points	Medium/High	Medium/Low	High/Low
2	23.63963057	22.745274	0.1559684
5	-6.17655748	42.60232	1.22120862
6	13.18026327	30.127104	0.51249255
7	21.40918084	23.841716	0.24323022
12	5.61881401	35.072335	0.78941558
15	5.72822689	34.728647	0.78880587
21	12.29905755	30.633618	0.54895541
25	8.90728105	32.877148	0.67106855
26	46.24385815	6.991107	-0.62667731

Figure 2 was compared with the OAO method, where most of the three data values are searched. The example in the first result, to find out the results of the prediction on line 2, first determine the class by comparing the first column, which is in the medium/high column with the data value 23.63963057, where there are only two classes which are positive for the medium class and negative for the high risk. The value of the first class is included in the medium class due to the positive value. In comparison, in the medium/low column, to find the next class, it is known that the value in row 2 column 2 is 22.745274, so the data value is included in the medium class because it is positive. Another example for classes in the high/low column, column 3 row 2, is known that the value of the data 0.15596840 is positive. The conclusion value in the third column is included in the high risk. From the comparison of the three columns (medium/high, medium/low and high/low), the results are in the form of 3 class data sequentially called low, medium, and high. From this class data, most of the class will be searched so that the class is in the second row (medium-risk). Figure 2 shows the prediction results obtained from the Kernel calculation of the data. The data were tested, displayed, visualized by certain colours and presented in maps, data, and graphics.

Validation

K-Fold cross-validation has been applied to see the performance of SVM in the classification process. Figure 3 shows the Kernel Fitting result for testing data. Although there are still outlier data over the classification process, the Kernel fitting showed that the performance of SVM in this data was 91.475% which is a good result to perform the clustering for hotspot data over time compared to other algorithms.

Furthermore, the Confusion matrix was also developed using the R package and resulting in the Confusion matrix inTable 3. From Table 3, the calculation of the accuracy for the SVM performance was 93.667%.

2	5	6	7	12	15	21	25	26	29	30	34	40	42
medium	high	medium	medium	medium	medium	medium	medium	medium	high	medium	high	medium	medium
44	56	62	65	73	82	84	85	86	88	101	110	111	113
medium	low	medium	medium	medium	medium	medium	medium	medium	high	high	medium	medium	medium
133	135	136	139	141	142	144	151	156	166	175	176	183	185
medium	medium	medium	high	high	medium	high	medium	medium	medium	high	medium	medium	medium
193	196	204	217	226	237	238	242	246	250	258	259	261	264
medium	high	medium	high	low	high	medium	high	medium	medium	medium	medium	high	medium
266	275	284	297	299	300	302	311	320	322	331	332	333	348
medium	medium	medium	medium	medium	low	medium	medium	medium	medium	medium	high	medium	medium
349	350	352	361	367	389	391	393	394	397	398	406	419	422
medium	medium	medium	medium	medium	high	medium	medium	medium	high	medium	high	low	medium
423	427	428	436	437	440	444	453	463	469	472	474	478	481
medium	medium	medium	medium	low	medium	medium	medium	medium	medium	low	medium	medium	medium

Figure 2. Prediction result

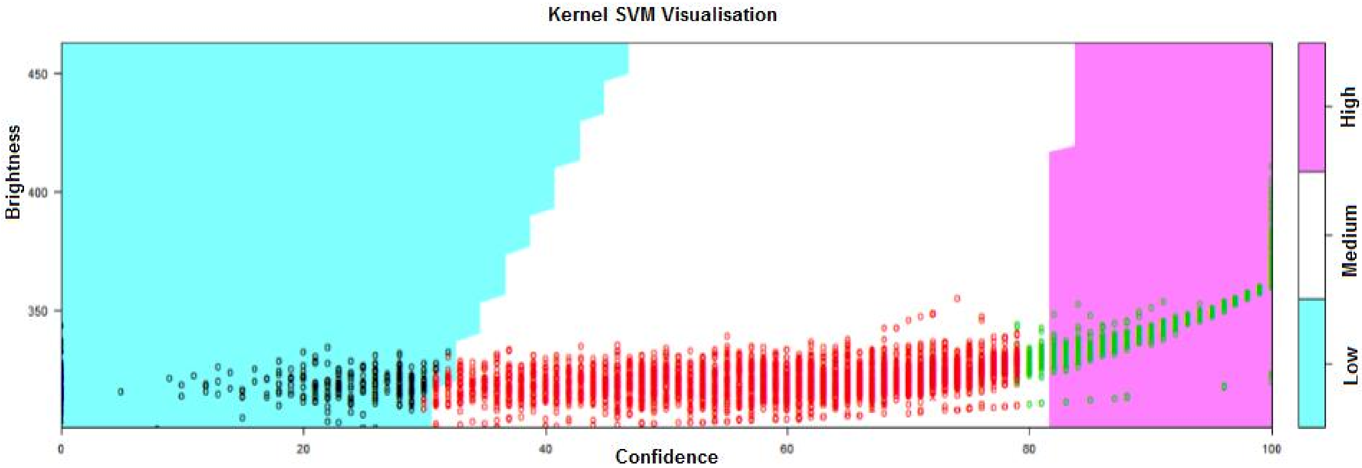

Figure 3. The Kernel fitting result

Table 3. Confussion matrix validation result

	High	Medium	Low
High	**23**	3	2
Medium	2	**302**	2
Low	1	4	**73**

3.2 Data Analysis

The classification process can be analysed based on the average brightness and confidence value from each point of the hotspot. From the data, this research concludes that the average value of brightness on the low-risk class was 318.6656852 with a confidence value of 18.0175419, the medium risks have an average value of brightness of 324.1567118 with a confidence of 58.4147162, the high-risk class has the average value of brightness on 339.2591721 and 88,8746856 on the confidence value. The emergence of hotspots has changed from year to year, as shown in Figure 4. Most of the hotspot data appeared on the year of 2019 (35.75%), and the number decreased significantly in 2020 (15.46%) when the pandemic of COVID-19 hit the world. The hotspot data were also clustered mostly on the medium risk (70.01%), and the lowest number of clusters was the low-risk class (10.05%). Furthermore, this research found that the occurrence of hotspot data was at its highest number in October when the lowest number was in January.

The increasing number of hotspots could be related to some of the parameters, including the access of roads and the palm oil expansion over Papua Island (Hambloch, 2022; Nelson et al., 2014). The Directorate General of Plantations, Ministry of Agriculture released the area of oil palm plantations in Indonesia by province, including Papua and West Papua. Meanwhile, the Director General of Plantations used temporary calculations in 2020 and estimated figures in 2021 (Ekawati et al., 2019; Fox et al., 2010). This data found that the area of oil palm plantations in Papua in 2018 reached 159.7 mHa and increased to 162.2 mHa in 2019. In 2020, the area will reach 51.8 mHa. Figure 4 shows that there is no significant expansion of oil palm plantations within a year (Runtuboi et al., 2021). However, the Tanah Papua Forest needs to be protected because it is Indonesia's last line of primary forest. This effort is also important to be supported by sustainable development policies so that environmental sustainability can be maintained. The distribution of hotspot locations over Papua Island showed interesting findings related to the palm oil plantation. The location of the high-risk hotspots was almost the same over time, where 24 palm oil companies expanded. The most significant number of high-risk class occurrences was in Merauke, Papua province. Although not all the fire hotspots indicated the place of palm oil, Figure 5 shows that the concentration of hotspot occurrences mainly appeared in the South of Papua Island.

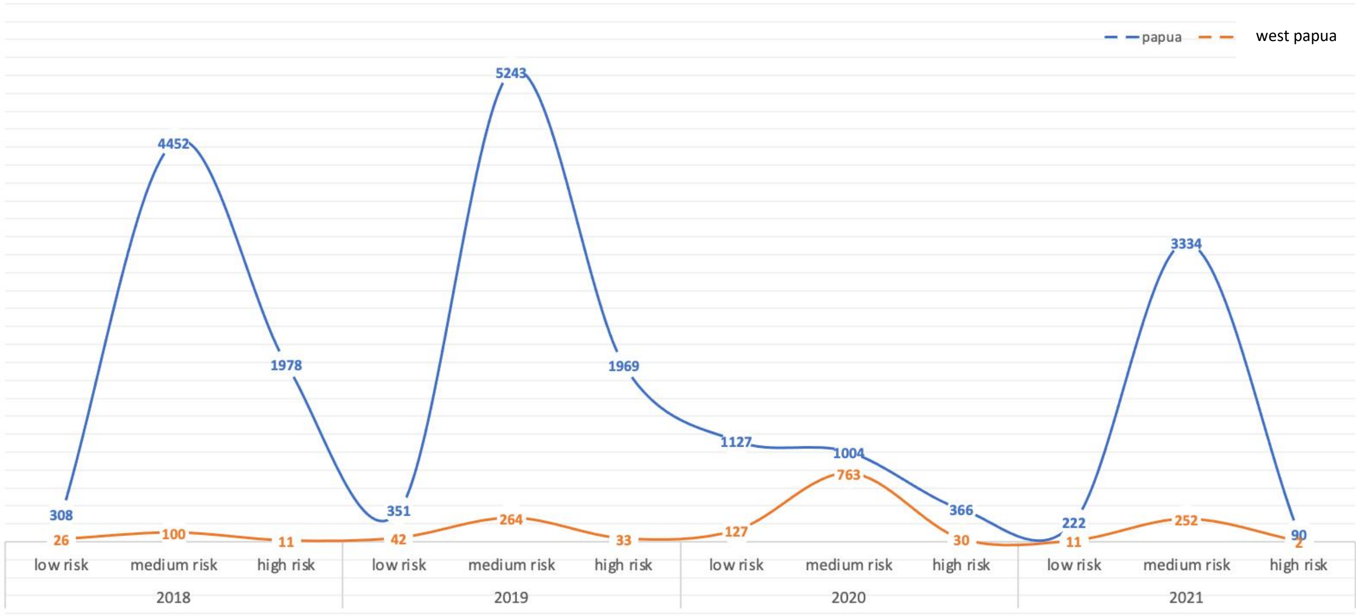

Figure 4. Hotspot occurrences based on class

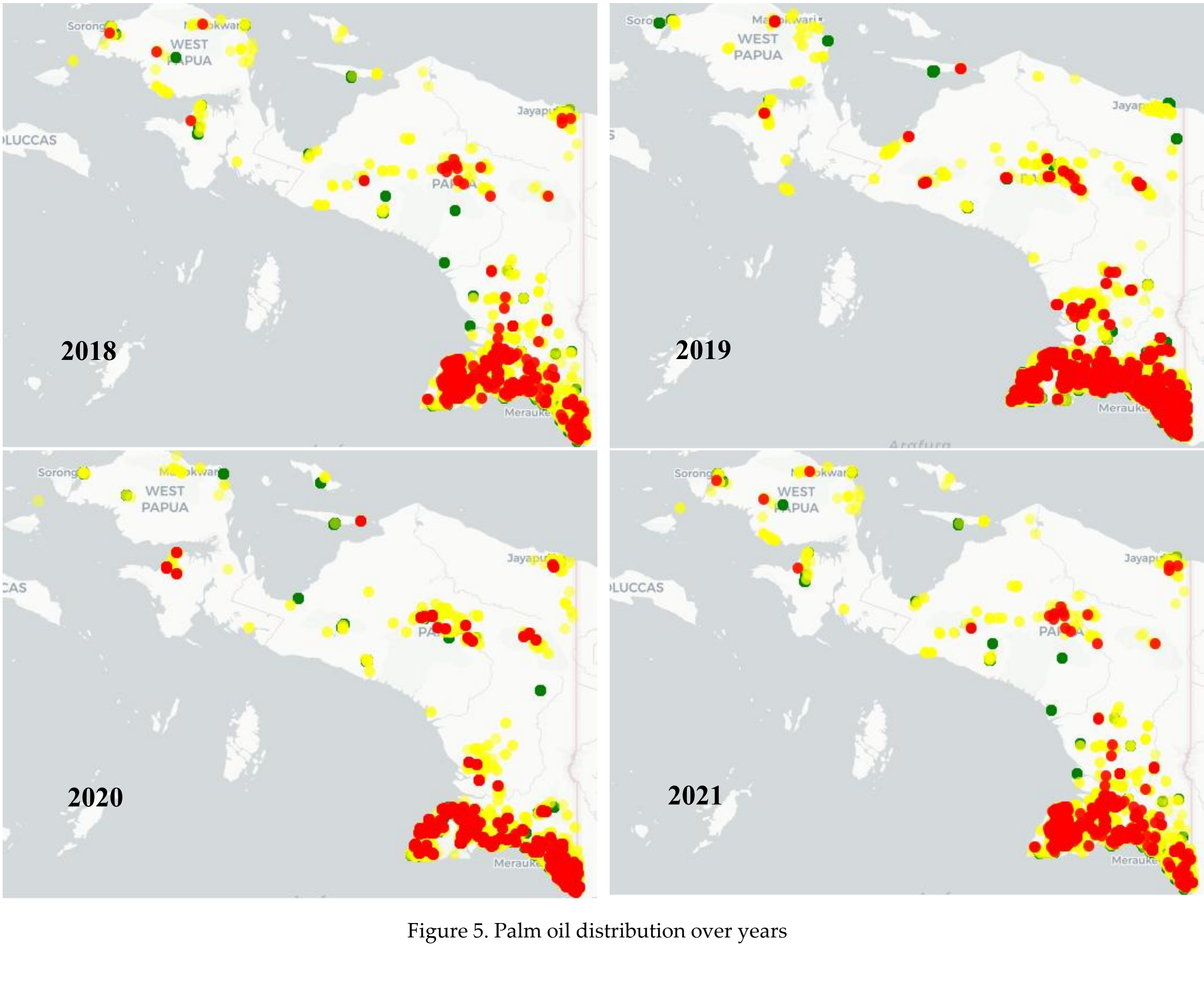

Figure 5. Palm oil distribution over years

Tropical forests in Papua continue to shrink due to degradation and the rate of forest destruction (deforestation). Sawit Watch cites data from the Government of the Republic of Indonesia that from 2005--2009 Papua's forest area was around 42.22 mHa. However, three years later (2011), it was degraded to the remaining was 30.07 mHa. The average deforestation in Papua is around 143,680 hectares per year. Meanwhile, the rate of deforestation in West Papua Province per year is, on average 293,000 Ha (25%). The Papua Provincial Government stated that the area of oil palm plantations in Papua in 2018 was 958,094.2 ha (not including West Papua). The land area is controlled by 79 oil palm plantation companies spread across various areas such as Merauke, Jayapura, Boven Digoel, Keerom, Sarmi, Waropen, Yahukimo, Nabire, Mimika, and Mappi. The largest area is in Merauke Regency and Boven Digoel Regency. The area of this oil palm plantation will continue to grow, considering that there is limited land in other areas such as Sumatra and Kalimantan. In addition, some policies will expand oil palm plantations in Papua to reach 5 mHa/year.

4. CONCLUSION

The Support Vector Machine (SVM) method can be implemented to classify potential forest or land fires based on hotspot data into three categories of forest or land fire risk levels: low, medium, and high. This research has succeeded in establishing an information system for fire potential detection using Papua Island hotspot data in 2018--2021 with the help of R Studio software that can be seen in areas with hotspots and potential fire classes with an accuracy level of 93.667%. The results of the analysis successfully pointed to the location of the emergence of hotspots is most visible in Merauke City, Tolikara City, and Puncak Jaya City in Papua. For further research, it is expected that the system can be used in real-time with longer data acquisition. Furthermore, additional Kernel functions can be used to improve the performance of the algorithms (Gaussian Kernel functions RBF, Sigmoid and Inverse Multi-quadratic Inverses).

ACKNOWLEDGEMENT

The authors would like to thanks for LPPM University of Bengkulu to make this research possible to be progress significantly. Additionally, we show our gratitude for Faculty of Engineering University of Bengkulu for the funding so this paper can be published in the journal.

REFERENCES

Aburomman, A. A., Ibne Reaz, M. & Bin. (2017). A novel weighted support vector machines multiclass classifier based on differential evolution for intrusion detection systems. *Information Sciences*, *414*. https://doi.org/10.1016/j.ins.2017.06.007.

Alita, D., Fernando, Y., & Sulistiani, H. (2020). Implementasi algoritma *multiclass svm* pada opini publik berbahasa Indonesia di *Twitter*. *Jurnal Tekno Kompak*, *14*(2). https://doi.org/10.33365/jtk.v14i2.792.

Andris, C., Cowen, D., & Wittenbach, J. (2013). Support Vector Machine for Spatial Variation. *Transactions in GIS*, *17*(1). https://doi.org/10.1111/j.1467-9671.2012.01354.x.

Benabdelkader, S., Melgani, F., & Boulemden, M. (2007). Cloud-contaminated image reconstruction with contextual spatio-spectral information. *International Geoscience and Remote Sensing Symposium (IGARSS)*, *1*, 373–376. https://doi.org/10.1109/IGARSS.2007.4422808.

Cui, J., Shi, G., & Gong, C. (2017). A fast classification method of faults in power electronic circuits based on support vector machines. *Metrology and Measurement Systems*, *24*(4). https://doi.org/10.1515/mms-2017-0056.

Ding, S., Zhu, Z., & Zhang, X. (2017). An overview on semi-supervised support vector machine. In *Neural Computing and Applications* (Vol. 28, Issue 5). https://doi.org/10.1007/s00521-015-2113-7.

Ekawati, S., Subarudi, Budiningsih, K., Sari, G. K., & Muttaqin, M. Z. (2019). Policies affecting the implementation of REDD+ in Indonesia (cases in Papua, Riau and Central Kalimantan). *Forest Policy and Economics*, *108*(September 2018), 101939. https://doi.org/10.1016/j.forpol.2019.05.025.

Fauvel, M., Chanussot, J., & Benediktsson, J. A. (2012). A spatial-spectral Kernel-based approach for the classification of remote-sensing images. *Pattern Recognition*, *45*(1), 381–392. https://doi.org/10.1016/j.patcog.2011.03.035.

Feng, Y., Liu, Y., & Batty, M. (2016). Modeling urban growth with GIS based cellular automata and least squares SVM rules: a case study in Qingpu–Songjiang area of Shanghai, China. *Stochastic Environmental Research and Risk Assessment*, *30*(5), 1387–1400. https://doi.org/10.1007/s00477-015-1128-z.

Forestry. (2015). Statistik Kementrian Lingkungan Hidup dan Kehutanan. *Pusat Data Infomasi Jakarta*, 1–20. https://doi.org/10.1017/CBO9781107415324.004.

Fox, J. C., Yosi, C. K., Nimiago, P., Oavika, F., Pokana, J. N., Lavong, K., & Keenan, R. J. (2010). Assessment of aboveground carbon in primary and selectively harvested tropical forest in papua New Guinea. *Biotropica*, *42*(4). https://doi.org/10.1111/j.1744-7429.2009.00617.x.

Gupta, S., Jaafar, J., & Ahmad, W. F. W. (2012). Static hand gesture recognition using local Gabor filter. *Procedia Engineering*, *41*. https://doi.org/10.1016/j.proeng.2012.07.250.

Hambloch, C. (2022). Land formalization turned land rush: The case of oil palm in Papua New Guinea. *Land Use Policy*, *112*. https://doi.org/10.1016/j.landusepol.2021.105818.

Heinzel, J., & Koch, B. (2012). Investigating multiple data sources for tree species classification in temperate forest and use for single tree delineation. *International Journal of Applied Earth Observation and Geoinformation*, *18*(1). https://doi.org/10.1016/j.jag.2012.01.025.

Hendri. (2019). Carbon management program in Papua region. *Jurnal Kehutanan Papuasia*, *1*(1). https://doi.org/10.46703/jurnalpapuasia.vol1.iss1.23.

Maione, C., Batista, B. L., Campiglia, A. D., Barbosa, F., & Barbosa, R. M. (2016). Classification of geographic origin of rice by data mining and inductively coupled plasma mass spectrometry. *Computers and Electronics in Agriculture*, *121*, 101–107. https://doi.org/10.1016/j.compag.2015.11.009.

Mather, P. M., & Koch, M. (2011). Classification. In *Computer Processing of Remotely-Sensed Images* (pp. 229–284). John Wiley & Sons, Ltd. https://doi.org/10.1002/9780470666517.ch8.

Mountrakis, G., Im, J., & Ogole, C. (2011). Support vector machines in remote sensing: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, *66*(3), 247–259. https://doi.org/10.1016/j.isprsjprs.2010.11.001.

Nelson, P. N., Gabriel, J., Filer, C., Banabas, M., Sayer, J. A., Curry, G. N., Koczberski, G., & Venter, O. (2014). Oil palm and deforestation in papua new Guinea. *Conservation Letters*, *7*(3). https://doi.org/10.1111/conl.12058.

Ozdarici, A., & Turker, M. (2007). Field-based classification of different resolution images and the filtering effects on the accuracies. *Proceedings of the 3rd International Conference on Recent Advances in Space Technologies, RAST 2007*, 321–325. https://doi.org/10.1109/RAST.2007.4284004.

Purnomo, H., Shantiko, B., Sitorus, S., Gunawan, H., Achdiawan, R., Kartodihardjo, H., & Dewayani, A. A. (2017). Fire economy and actor network of forest and land fires in Indonesia. *Forest Policy and Economics*, *78*. https://doi.org/10.1016/j.forpol.2017.01.001.

Rawashdeh, G., Mamat, R. Bin, Bakar, Z. B. A., & Rahim, N. H. A. (2019). Comparative between optimization feature selection by using classifiers algorithms on spam email. *International Journal of Electrical and Computer Engineering*, *9*(6). https://doi.org/10.11591/ijece.v9i6.pp5479-5485.

Riyanto, I. A., Cahyadi, A., Kurniadhini, F., Bachtiar, H., Apriyana, D., & Caraka, B. K. A. (2020). Understanding Forest Fire Management in Indonesia from a Global Perspective. *ASEAN Journal on Science and Technology for Development*, *37*(1). https://doi.org/10.29037/ajstd.593.

Rowe, C., David, B., Mialanes, J., Ulm, S., Petchey, F., Aird, S., McNiven, I. J., Leavesley, M., & Richards, T. (2020). A Holocene record of savanna vegetation dynamics in southern lowland Papua New Guinea. *Vegetation History and Archaeobotany*, *29*(1). https://doi.org/10.1007/s00334-019-00724-7.

Runtuboi, Y. Y., Permadi, D. B., Sahide, M. A. K., & Maryudi, A. (2021). Oil palm plantations, forest conservation and indigenous peoples in west papua province: what lies ahead? *Forest and Society*, *5*(1). https://doi.org/10.24259/fs.v5i1.11343.

Tasurruni, T., Nugroho, B., & Maturbong, R. A. (2019). Kajian pelaksanaan kegiatan pencegahan kebakaran hutan dan lahan di Provinsi Papua Barat. *Cassowary*, *2*(2). https://doi.org/10.30862/casssowary.cs.v2.i2.26.

Torabzadeh, H., Leiterer, R., Hueni, A., Schaepman, M. E., & Morsdorf, F. (2019). Tree species classification in a temperate mixed forest using a combination of imaging spectroscopy and airborne laser scanning. *Agricultural and Forest Meteorology*, *279*. https://doi.org/10.1016/j.agrformet.2019.107744.

Tsutsumida, N., & Comber, A. J. (2015). Measures of spatio-temporal accuracy for time series land cover data. *International Journal of Applied Earth Observation and Geoinformation*, *41*, 46–55. https://doi.org/10.1016/j.jag.2015.04.018.