Indonesian Journal of Data Risk Research, 2026, Vol.1, No.1, Page 58-72.

Contents lists available at Indonesian Scholar Society

Indonesian Journal of Data Risk Research

Journal Homepage:
https://journal.solusiriset.com/index.php/ijdrr/index

e-ISSN: xxxx-xxxx

Smoke Detection Algorithm on Digital Image Sequences Using Gaussian Mixture Model (GMM) Segmentation Method and Region Growing for Fire Detection System

Fitri Nur Azizah[1], Djoko Heksa Purnomo[2,*]

[1] Indonesian Army, Indonesia

[2] Department of Mathematics, Indonesia Defense University, Indonesia

Corresponding Email: djoko.heksa@idu.ac.id

A B S T R A C T

Although various fire prevention efforts have been made, fire incidents continue to occur in various regions. To minimize the risk of these fires, a quick response is necessary so that mitigation efforts can be promptly carried out. This can be achieved by implementing a fire detection system. In such a system, smoke detection is one of the key elements aimed at providing a quick response to potential fire hazards. The development of a smoke detection algorithm is therefore crucial for enhancing the performance of the fire detection system. This study proposes a smoke detection algorithm that combines the Gaussian Mixture Model (GMM) segmentation method and region growing. The input data is in the form of video, which undergoes various preprocessing steps to prepare the data in the required format. Then, in the processing stage, two segmentation steps are carried out: GMM segmentation and region growing. GMM segmentation focuses on dividing the regions in the image into several clusters. Meanwhile, the region growing process is applied to expand the regions identified as smoke by considering the spatial context of the pixels. The output generated is a binary image with smoke objects in white and the background in black. Visually, the algorithm shows that the proposed approach is capable of providing better smoke detection compared to single segmentation methods. The results of this study demonstrate the potential of the smoke detection algorithm using GMM and region growing segmentation in improving the performance of fire detection systems.

ARTICLE INFO

Received
9 Feb 2026
Revised
11 March 2026
Accepted
28 Mei 2026

Keywords: CCTV; Detection Algorithm; GMM Segmentation; Image Segmentation; Region Growing; Smoke Detection.

I. INTRODUCTION

Fires are an incessant occurrence in this homeland, whether it be house fires, building fires, or even forest fires. Fires often threaten human life, infrastructure, and ecological systems [1]. Fires can occur in residential areas and result in casualties and material losses with significant monetary value. Fires can also occur in open areas such as agricultural land and forests; of course, this will cause losses, including the loss of natural potential such as trees, which are the main producers of oxygen and can be utilized by humans to meet needs such as building materials, food, medicine, and others. In addition, the smoke produced by the fire also has a very detrimental impact on human health [2]. If the fire lasts for a long time and produces a large amount of smoke, it can result in widespread haze events that hinder various economic activities in the community [3]. These points indicate that fires pose a threat to national resilience, particularly in the fields of economy, health, and the environment.

The Indonesian National Police (2023) reported 1,167 fire incidents from January to June 2023. According to data from the Ministry of Environment and Forestry (2023), during the period from January to July 2023, the area of forest and land fires (karhutla) in Indonesia reached 90,405 hectares (ha). All of those fires were recorded to have produced emissions of more than 5.9 million tons of carbon dioxide equivalent (CO_2). Based on that data, it is evident that the fires are becoming more massive. Therefore, the solution needed is not only preventive measures but also efforts to minimize the risks caused by unavoidable fires, known as disaster mitigation. Efforts that can be made to minimize the risk of fire can be carried out by quickly detecting the fire so that mitigation can be implemented immediately before the resulting losses become greater [4].

Therefore, technology is needed to detect the existence of a fire early, known as a fire detection system. A fire detection system is a collection of several integrated technologies used to detect fires early [5]. The system consists of several types based on the adopted sensors, including smoke, heat, light, and hazardous gas detection sensors related to fires. When these sensors detect indications of a fire, the system will activate emergency signals such as fire alarms or call the fire department [6].

Digital image processing techniques are classified by objective, including filtering, image smoothing, masking, image transformation, extraction, segmentation, reconstruction, and pattern or object recognition. Object recognition is an image processing technique aimed at identifying the presence and types of objects in an image [7]. Segmentation and object recognition are techniques often used in digital camera-based fire detection systems. In this case, the most important object to identify is smoke, as the presence of smoke indicates the presence of a fire.

There are various smoke detection methods in images that have been developed by previous researchers. [8] identified smoke using segmentation techniques with a method combining motion characteristics and color feature extraction. [9] also used the same method as [8], but produced better output. Nevertheless, the method still produced errors in detecting smoke objects. In 2016, [10] used the active contour and threshold techniques in her research to detect smoke. This method was quite good at identifying smoke, but it still caused inaccuracies in smoke identification in complex-colored images, such as images of nature. [11] proposed a smoke image segmentation method using the K-Means Clustering method. Although segmentation with K-Means Clustering can be done quickly, the segmentation results are not precise, especially for images with high color variation. In addition, in the same year, [12] combined the rough set theory method and region growing in their research on smoke detection. The segmentation results provided by the method were good, but they required a relatively long computation time. Based on the aforementioned studies, further development of the method is still needed to improve the segmentation of smoke objects.

Based on this background, this research will develop a smoke detection technique using segmentation and object recognition methods. This method combines segmentation techniques to simplify color variations in images using the Gaussian Mixture Model (GMM) method with the Expectation-Maximization (EM) algorithm, followed by region-growing techniques with initialization points performed using smoke object recognition techniques.

II. METHODS

1. Digital Image Processing

Information or data is not only presented in text form, but can also be in the form of images. Digital image processing is a general term for techniques aimed at manipulating or improving images [13]. In general, the objectives of digital image processing include the following.

a. Improving the quality of the image to emphasize certain information contained within the image.
b. Performing recognition or classification of objects contained in the image.
c. Dividing parts of the image so that they can be removed or combined with other parts of the image.

Image processing helps obtain more meaningful information from image data, facilitating better interpretation and analysis. Techniques in image processing continue to evolve along with technological advancements, such as visual computing and artificial intelligence [14]. Operations that can be performed in digital image processing include image enhancement, image restoration, image segmentation, image analysis, image reconstruction, pattern recognition, etc [15].

Image segmentation is an operation in digital image processing that aims to divide the image into several segments based on certain criteria [15]. There are many segmentation techniques, including thresholding, Hough transform, connected component labeling, cluster-based segmentation, and others. The segmentation technique commonly used in object detection research is cluster-based segmentation. This technique uses data from each pixel of the image and groups them into several clusters, generally based on the proximity of the pixels to each other [16].

2. Digital Video Processing

A series of digital images displayed in sequence will produce a digital video. A digital video is an electronic representation of moving visual images (video) in digital data format. Unlike an image that consists of only a single picture or a single image, digital video consists of a series of images, as illustrated in Figure 1.

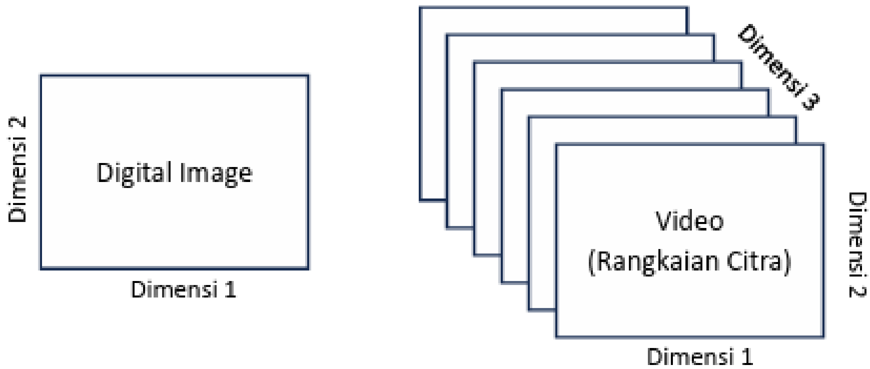


Figure 1. Dimensions of Digital Images and Video

Digital video processing is not much different from digital image processing, but digital video contains more information than static images. This is because digital video is a series of images, and motion is captured in the image series or digital video. An image is simply a capture of an object that forms a single image, while digital video or a series of images is a series of several images that provide a snapshot of an object and record its dynamics. The movement and dynamics recorded in the image series make it easier to identify an object even if the object is not clearly visible in the static image [7].

3. Gaussian Mixture Model (GMM)

A Gaussian Mixture Model (GMM) is a probabilistic model used to create a data distribution model using the Gaussian distribution as a component of the mixture model. For example, $x_1, x_2, \dots, x_n$ is a collection of pixels in an image that is considered to have a Gaussian mixture distribution or Gaussian Mixture Model [17], [18]. Each Gaussian component in GMM has main parameters, namely, the mean as the cluster center in the feature space, the covariance that indicates how isolated the variables are in the cluster, and the weights that provide information about the relative contribution of each Gaussian component to the overall distribution [19].

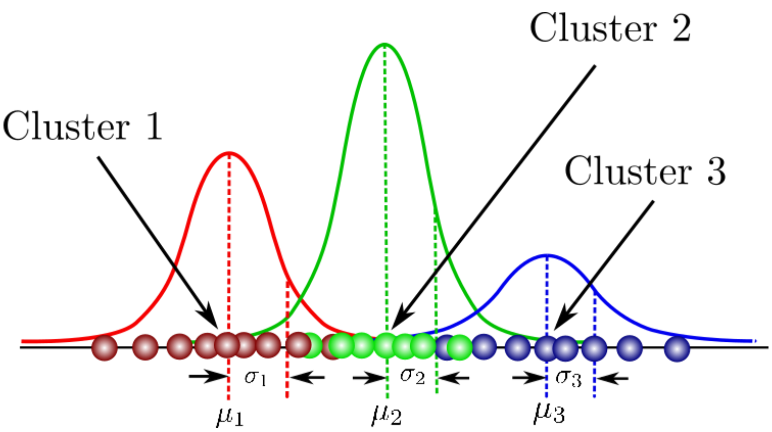


Figure 2. Illustration of Gaussian Model Parameters with the Number of Components $K = 3$

The Gaussian Mixture Model (GMM) density function is a mathematical representation of the probability of data in the model. This function describes how data is distributed in a dimensional space based on a mixture of several Gaussian components. The GMM density function expresses the sum of individual Gaussian components weighted by the proportion of each component. In general, the GMM density function is expressed as follows:

$$p(x|\theta) = \sum_{k=1}^{K} \pi_k f(x|\mu_k, \Sigma_k) \tag{1}$$

with

$$f(x|\mu_k, \Sigma_k) = \frac{1}{(2\pi)^{\frac{d}{2}}|\Sigma_k|^{\frac{1}{2}}} e^{-\frac{1}{2}(x-\mu_k)^T \Sigma_k^{-1}(x-\mu_k)} \tag{2}$$

where $p(x|\theta)$ is the probability density function for the data point x with parameter θ. K is the number of Gaussian components. π_k is the prior weight for the k-th Gaussian component. $f(x|\mu_k, \Sigma_k)$ is the probability density function of the k-th Gaussian component with mean μ_k and covariance matrix Σ_k.

4. Expectation-Maximization Algorithm (EM)

Dempster, Laird, and Rubin first introduced the Expectation-Maximization (EM) algorithm in 1977 [20]. EM is an algorithm with an iterative method to obtain estimations (expectations), and the maximum likelihood function will yield good results. This iterative method will provide Maximum Likelihood results, which generate new parameter values, namely mixture weights, means, and covariances or standard deviations [21]. There are two stages in each iteration of the EM algorithm, namely the expectation stage (E-Step) and the maximization stage (M-Step), generally explained as follows [22].

1. E-Step
   At this stage, the estimation of the expected value or expectation of a variable is performed based on the observed data and known parameters. The E-Step calculates the conditional distribution of the variable, known as responsibility, which indicates that each data point in the sample originates from each component in the model.
2. M-Step
   At this stage, the model parameters (mean, covariance, and weights) are updated with the aim of maximizing the expected function calculated in the E-Step. The M-Step performs an optimization process to obtain the parameter values that can maximize the likelihood function while considering the responsibilities.

5. Region Growing

Region growing is one of the segmentation techniques that groups pixels or subregions into larger areas based on defined criteria. The basic approach starts from a set of initial points [23]. After that, the area will grow larger with the addition of adjacent pixels that have similar properties to those points. The goal of region-based segmentation is to group several areas or objects from an image.

6. Segmentation using the Gaussian Mixture Model (GMM) method with the Expectation-Maximization (EM) algorithm

At this segmentation stage, GMM parameters are initialized, including determining the number of Gaussian components and the mean, covariance, and weight parameters for each component. This is followed by the estimation stage using the EM algorithm, which includes calculating the responsibility of each data point/pixel toward each Gaussian component and updating the mean, covariance, and weight parameters. This estimation stage is carried out until the model has converged. Model convergence is considered based on the difference in log-likelihood from the models obtained from two consecutive iterations [24]. If the difference in log-likelihood is greater than the threshold value, then the last model is still not converged, and the next iteration continues. Conversely, if the difference in log-likelihood is less than the threshold, then the model has converged. When the model has converged, the next step is to determine the clusters based on the Gaussian distribution obtained from the GMM. This separation is determined based on the highest probability that each pixel has of being part of the cluster, resulting in a segmented image.

7. Segmentation with the Region Growing Method

After image segmentation using the GMM method, the image undergoes further segmentation using the region-growing method. In this method, there are two important aspects, namely the initialization of the starting point or seed and the determination of the threshold. A seed is a point that serves as the starting point, which then develops into a region or object based on the similarity of pixel intensity criteria through a threshold value [23]. In determining the seed point, the aspects that need to be analyzed are motion extraction and color feature extraction on the original image.

Figure 3 presents the research flow, which serves as a guideline for implementing this study and systematically represents each stage of the research.

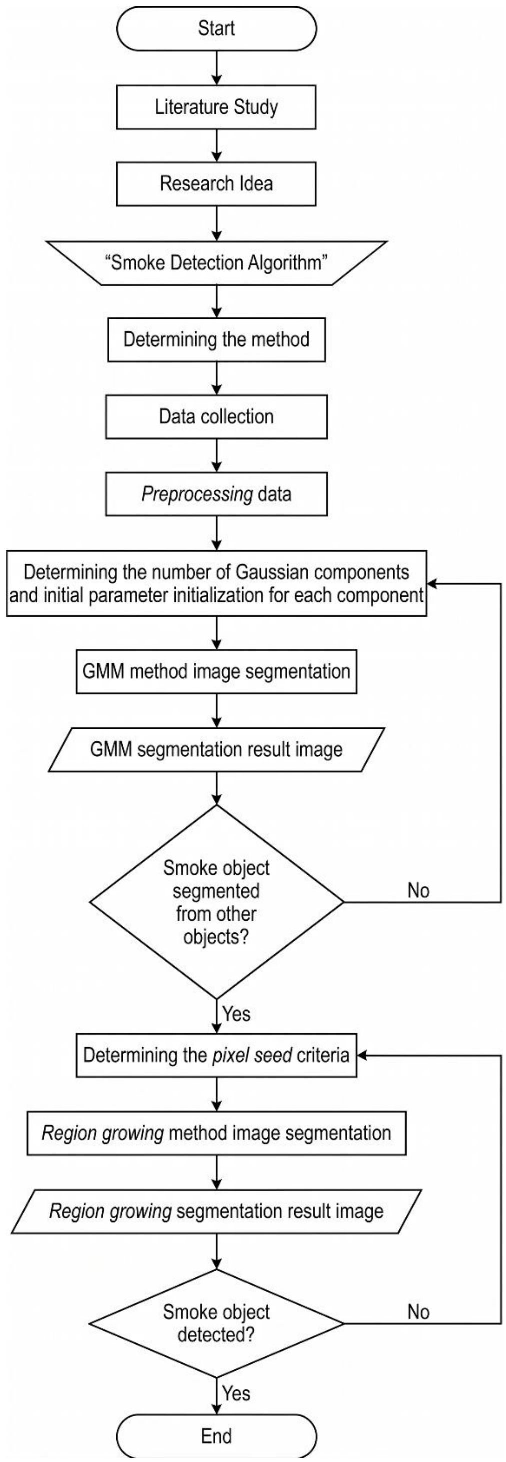
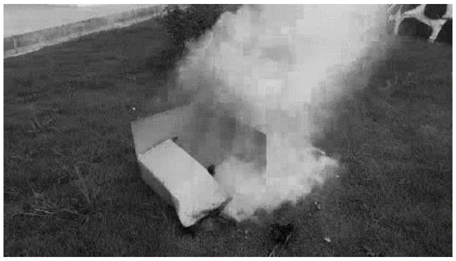


Figure 3. Research Flowchart

III. RESULTS AND DISCUSSION

The input data is video, which is then converted into a series of static images, also known as frames. After the frames are obtained, the frame format is converted from RGB to grayscale, and the frames are resized to 450x800 (videos 1 and 2) and 600x800 (video 3). These steps are part of the preprocessing stage. Figure 4(b) shows the result of the preprocessing stage.

(a)

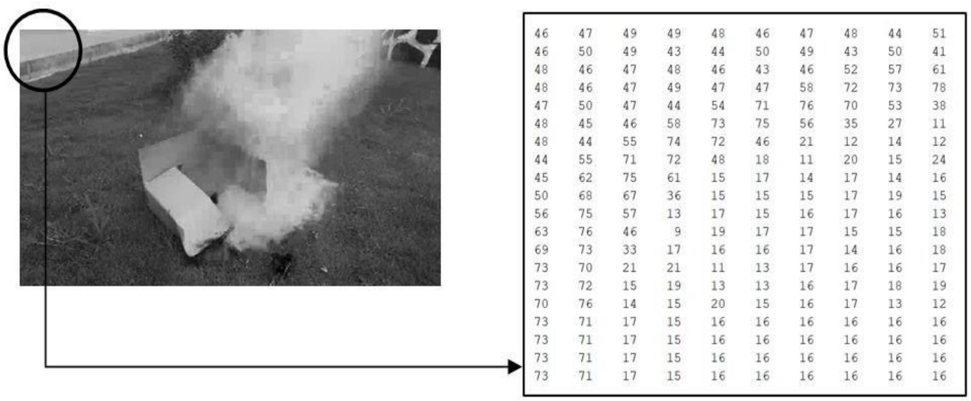


(b)

Figure 4. (a) Original Frame, and **(b)** Frame After Resizing and Grayscaling

The preprocessing stage is the phase carried out to convert the input video into a format that is more ready to be processed and analyzed in the processing stage. The first process carried out at this stage is the conversion of the video into a dataframe or a series of static images. After that, the images are resized to 450x800 (for videos 1 and 2) and 600x800 (for video 3), with the aim of speeding up processing time, making the resizing step optional.

The final process in preprocessing is converting the RGB image format, which consists of 3 color components (red, green, and blue), into grayscale, as shown in Figure 6(c), with the aim of simplifying the segmentation process. Thus, each pixel only has 1 grayscale value. The grayscale value of each pixel in the image, as seen in Figure 5(b), will be used in the next process.



46	47	49	49	48	46	47	48	44	51
46	50	49	43	44	50	49	43	50	41
48	46	47	48	46	43	46	52	57	61
48	46	47	49	47	47	58	72	73	78
47	50	47	44	54	71	76	70	53	38
48	45	46	58	73	75	56	35	27	11
48	44	55	74	72	46	21	12	14	12
44	55	71	72	48	18	11	20	15	24
45	62	75	61	15	17	14	17	14	16
50	68	67	36	15	15	15	17	19	15
56	75	57	13	17	15	16	17	16	13
63	76	46	9	19	17	17	15	15	18
69	73	33	17	16	16	17	14	16	18
73	70	21	21	11	13	17	16	16	17
73	72	15	19	13	13	16	17	18	19
70	76	14	15	20	15	16	17	13	12
73	71	17	15	16	16	16	16	16	16
73	71	17	15	16	16	16	16	16	16
73	71	17	15	16	16	16	16	16	16
73	71	17	15	16	16	16	16	16	16

(a) **(b)**

Figure 5. (a) Image, and **(b)** Gray Level

The next stage is processing. The process carried out at this stage is image segmentation, so that the smoke object in the image is identified. The method used for image segmentation is region growing. This method has several advantages, including good segmentation capability, adaptability to intensity variations, fast performance, and minimal user interaction (only requiring the initialization of initial parameters). However, using region growing as a single method in the smoke detection algorithm has not yet provided the best results, as seen in Figure 6(b). Therefore, a segmentation method that can be combined with region growing is needed so that the output is better than the single method.

(a) **(b)** **(c)**

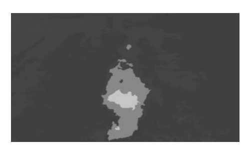
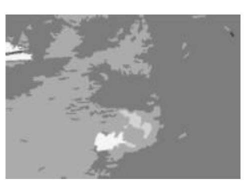
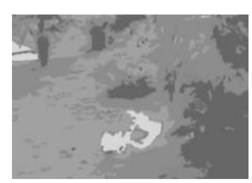
Figure 6. (a) Original Image, **(b)** Example of Single Method Image Segmentation Results, and **(c)** Example of Multiphase Segmentation Method Segmentation Results

In this study, image segmentation methods are combined with region growing, including methods with a Rough Set Theory approach, K-Means clustering method, and GMM method. The computation time for each method and the image segmentation results can be seen in Tables 1 and 2.

Table 1. Comparison of Computation Time (s) for Each Method

Rough Set Theory	K-Means Clustering	Gaussian Mixture Model
10.342278	3.534549	6.265866
9.748589	3.020081	3.275393
9.875349	3.473774	5.687795

Table 2. Image Segmentation Results

Original Image	Rough Set Theory	K-Means Clustering	Gaussian Mixture Model
			
			
			

Tables 1 and 2 show the image segmentation results along with the computation time required by the three methods. In terms of computation time, the K-Means method excels, but the segmentation results are unstable in several trials, as seen in Table 2. Meanwhile, Table 1 also shows that the Rough Set Theory method requires a considerable amount of computation time. Therefore, this research combines the GMM method and region growing to detect smoke in digital images.

Table 3. Image Segmentation Results Using the GMM Method and Computation Time with the Number of Gaussian Components 3, 4, and 5

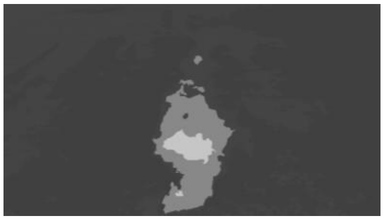
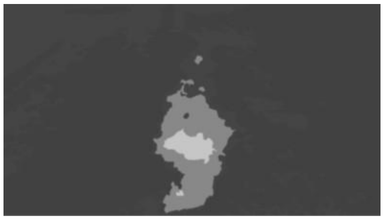
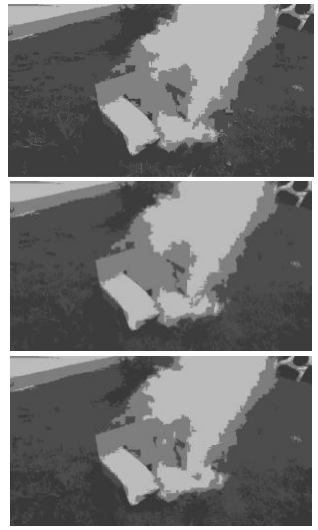
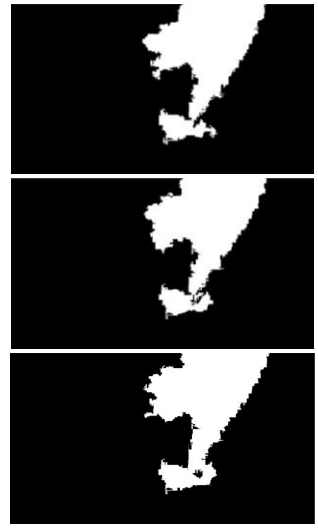
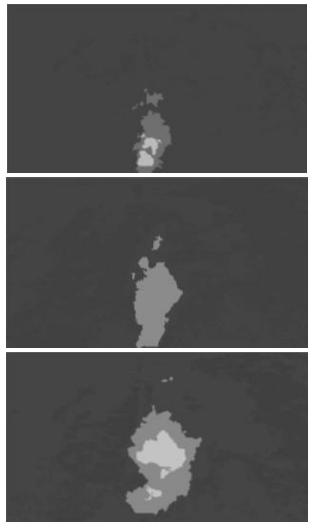
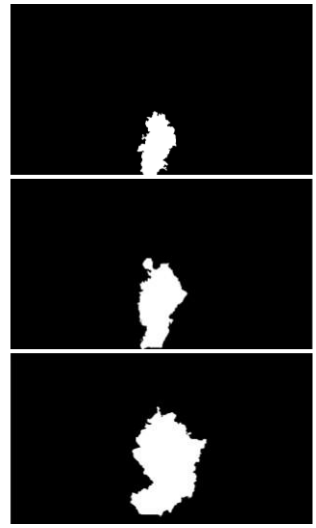
Number of Components	Output	Computation Time (s)
5		4.234331
4		2.092062
3		1.215389

Table 3 shows that the GMM segmentation results with 3 components are not good enough for clustering, especially the smoke objects in the image, while 5 components yield good results, but the computation time is longer. Therefore, the number of components used is 4.

Table 4. GMM Stage Segmentation Results and GMM Segmentation Results and Region Growing

Data	Original Image	GMM Segmentation Results	GMM and RG Segmentation Results
Video I			
Video II			

Data	Original Image	GMM Segmentation Results	GMM and RG Segmentation Results
Video III			

There are two segmentation stages to detect smoke objects in the image, namely, the GMM method segmentation stage, followed by the region-growing method segmentation stage. The GMM segmentation results can be seen in Figure 7.

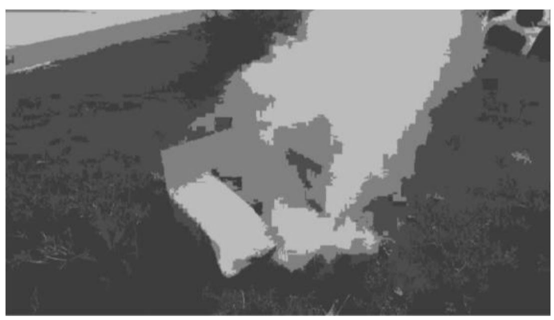


Figure 7. GMM Segmentation Results

After the region-growing segmentation stage is complete, the next step is to build the output image in the form of a segmented smoke image, where pixels with a value of 1 will be white and indicate the smoke area, while pixels with a value of 0 will be black and indicate objects other than smoke or the background, as shown in Figure 8.

Figure 8. Final Result of Smoke Detection Algorithm

IV. CONCLUSION

This research aims to develop a smoke detection algorithm within a fire detection system. The proposed algorithm combines two segmentation methods, namely, the Gaussian Mixture Model (GMM) and region growing. Experimental results show that the combination of GMM segmentation and region growing is capable of producing good smoke detection. In the application of the smoke detection algorithm, GMM segmentation is iteratively applied to group the elements of each pixel in the grayscale image into four clusters so that the elements representing the smoke object will be in a separate cluster from the other elements. Thus, it will facilitate the smoke detection process in the next step. Meanwhile, the region growing method is applied to identify areas that potentially contain smoke in the image and are designated as seeds, which are then expanded based on specified criteria. In this case, the region growth criterion is the similarity of the cluster of neighboring elements with the seed; if the neighboring pixels belong to the same cluster, then those pixels join the seed to form a growing region.

Visually, the proposed algorithm can detect smoke objects. However, further testing and validation are still needed on a larger scale and in more realistic environmental conditions. Field data acquisition involving real fire situations can provide valuable insights into the algorithm's performance in real-world scenarios.

V. AUTHOR CONTRIBUTION

The authors contributed equally to the formulation of the research concept, data collection, data analysis, manuscript writing, and approval of the final manuscript for publication.

VI. CONFLIC OF INTEREST

The authors declare that there are no potential conflicts of interest related to the research, writing, or publication of this article.

REFERENCES

[1] R. L. Schumann *et al.*, “Wildfire recovery as a ‘Hot moment’ for creating fire-adapted communities,” *International Journal of Disaster Risk Reduction*, vol. 42, p. 101354, Jan. 2020, doi: 10.1016/j.ijdrr.2019.101354.

[2] P. Mulia, Nofrizal, and W. N. Dewi, “Analisis dampak kabut asap karhutla terhadap gangguan kesehatan fisik dan mental,” *HEALTH CARE : JURNAL KESEHATAN*, vol. 10, no. 1, 2021, doi: 10.36763/healthcare.v10i1.103.

[3] Hairani, “Implementasi prinsip state responsibility dalam pencemaran kabut asap lintas negara (Transboundary haze pollution) di Indonesia,” Universitas Syiah Kuala, 2019.

[4] A. Molina-Pico, D. Cuesta-Frau, A. Araujo, J. Alejandre, and A. Rozas, “Forest monitoring and wildland early fire detection by a hierarchical wireless sensor network,” *J. Sens.*, vol. 2016, pp. 1–8, 2016, doi: 10.1155/2016/8325845.

[5] M. Ruslan, M. S. Al-Amin, and E. Emidiana, “Perancangan sistem fire alarm kebakaran pada gedung laboratorium XXX,” *Jurnal Tekno*, vol. 18, no. 2, pp. 51–61, Nov. 2021, doi: 10.33557/jtekno.v18i2.1412.

[6] Z. Liu, “Review of recent developments in fire detection technologies,” *Journal of Fire Protection Engineering*, vol. 13, no. 2, pp. 129–151, May 2003, doi: 10.1177/1042391503013002003.

[7] A. Bovik, “Handbook of image & video processing,” *Academic Press*, vol. 369, no. 1, 2013.

[8] L. Mengxin, W. Xu, K. Xu, J. Fan, and D. Hou, “Review of fire detection technologies based on video image,” 2013.

[9] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2016. doi: 10.1109/CVPR.2016.90.

[10] F. S. Najiha, “Deteksi asap rokok menggunakan segmentasi color Image processing,” 2016.

[11] M. Shrivastava and P. Matlani, “A smoke detection algorithm based on K-means segmentation,” in *2016 International Conference on Audio, Language and Image Processing (ICALIP)*, IEEE, Jul. 2016, pp. 301–305. doi: 10.1109/ICALIP.2016.7846590.

[12] H. Wang and Y. Chen, “A smoke image segmentation algorithm based on rough set and region growing,” *J. For. Sci. (Prague).*, vol. 65, no. 8, pp. 321–329, Aug. 2019, doi: 10.17221/34/2019-JFS.

[13] Arnita, F. Marpaung, F. Aulia, N. Suryani, and R. C. Nabila, *Computer Vision dan Pengolahan Citra Digital*. Pustaka Aksara, 2022.

[14] F. Dufaux, “Grand challenges in image processing,” *Frontiers in Signal Processing*, vol. 1, Apr. 2021, doi: 10.3389/frsip.2021.675547.

[15] R. Munir, *Pengolahan Citra Digital dengan Pendekatan Algoritmik*. Bandung: Informatika Bandung, 2004.

[16] G. Ramella and G. S. di Baja, “Color histogram-based image segmentation,” 2011, pp. 76–83. doi: 10.1007/978-3-642-23672-3_10.

[17] N. Iriawan, “Pemodelan mixture of mixture dalam pemilihan portofolio,” in *Prosiding Seminar Nasional Statistika Universitas Diponegoro*, 2011.

[18] G. J. McLachlan and D. Peel, *Finite mixture models 2000*. Wiley, 2000.

[19] T. M. Nguyen and Q. M. J. Wu, “Dirichlet Gaussian mixture model: Application to image segmentation,” *Image Vis. Comput.*, vol. 29, no. 12, pp. 818–828, Nov. 2011, doi: 10.1016/j.imavis.2011.09.001.

[20] A. P. Dempster, N. M. Laird, and D. B. Rubin, “Maximum likelihood from incomplete data via the EM algorithm,” *Journal of the Royal Statistical Society*, vol. 39, no. 1, pp. 1–38, 1977, [Online]. Available: http://www.jstor.org/stable/2984875

[21] L. Handayani, “Identifikasi area kanker ovarium pada citra CT SCAN abdomen menggunakan metode Expectation Maximization,” *Seminar Nasional Teknologi Informasi Komunikasi dan Industri (SNTIKI) 4*, 2012.

[22] Y. Pu, J. Sun, N. Tang, and Z. Xu, “Deep expectation-maximization network for unsupervised image segmentation and clustering,” *Image Vis. Comput.*, vol. 135, p. 104717, Jul. 2023, doi: 10.1016/j.imavis.2023.104717.

[23] H. Wang and Y. Chen, “A smoke image segmentation algorithm based on rough set and region growing,” *J. For. Sci. (Prague).*, vol. 65, no. 8, pp. 321–329, Aug. 2019, doi: 10.17221/34/2019-JFS.

[24] J. Qiao *et al.*, “Data on MRI brain lesion segmentation using K-means and Gaussian Mixture Model-Expectation Maximization,” *Data Brief*, vol. 27, p. 104628, Dec. 2019, doi: 10.1016/j.dib.2019.104628.