JURNAL ECOTIPE
Electronic, Control, Telecommunication, Information, and Power Engineering
Volume 11, Issue 2, October 2024, pp. 134-142
ISSN 2355-5068 ; e-ISSN 2622-4852
DOI: 10.33019/jurnalecotipe.v11i2.4499

Testing Smoker Detection Using Google Cloud Services and Infrastructure

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ARTICLE INFO

Article historys:

Received : 03/07/2024
Revised : 29/07/2024
Accepted : 01/08/2024

Keywords:

Cloud Computing; Deep Learning; Google Cloud Vision API; Image Processing; Smoker Detection

ABSTRACT

Smoking remains a significant public health challenge globally, contributing to a wide range of detrimental health outcomes, including cardiovascular diseases, cancer, and respiratory disorders. Despite concerted efforts to curb smoking rates through policy interventions, effective monitoring and enforcement remain complex and resource-intensive tasks for health authorities and organizations. Innovative approaches leveraging advanced technologies, such as visual detection systems powered by deep learning, offer promising solutions to enhance smoking behavior detection and monitoring. Integrating the Google Cloud Vision API enables real-time identification of smoking indicators and discrimination from complex visual backgrounds. This capability supports proactive health monitoring and strengthens the enforcement of public health policies aimed at reducing smoking prevalence. The research methodology utilizes a dataset of 600 images sourced from the Kaggle platform, encompassing diverse scenarios to optimize model training. Techniques such as image segmentation, feature extraction, and machine learning-based classification are employed to achieve high levels of precision and recall in identifying smokers and cigarette smoke. The model achieved a precision of 96% and a recall of 96%, indicating its high accuracy in identifying smokers. However, the study acknowledges challenges such as bandwidth constraints and security risks associated with handling sensitive health data. Nevertheless, technological innovations in visual detection systems and cloud services are pivotal in mitigating the health impacts of smoking and advancing public health initiatives.

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1. INTRODUCTION

The presence of cigarettes has become a complex and controversial topic with significant impacts on public well-being. While smoking is legal, its effects extend beyond individual smokers. Cigarette smoke, whether in open spaces or enclosed environments like workplaces, restaurants, or public transportation, poses discomfort and health risks to those exposed. Long-term effects include increased risks of serious illnesses such as lung cancer, heart disease, and respiratory disorders.

Previous research has shown that technology offers promising solutions to address these health impacts. For example, a study by Kahendra explored factors affecting the implementation of smoke-free area policies and highlighted the need for effective monitoring systems to support these policies[1]. Another study by Gojali and Tjiong developed an application using the YOLOv3 algorithm to detect smoking activities, demonstrating the potential of visual detection systems in identifying smokers and cigarette smoke in various settings[2].

In line with these findings, visual detection systems using cameras and image processing algorithms can swiftly and accurately identify smokers and cigarette smoke. These algorithms, powered by deep learning, enable cameras to recognize smoking behaviors and distinguish cigarette smoke from the visual background. Integrated with health monitoring systems or public alert mechanisms, such technology provides real-time, precise information on cigarette presence in public spaces, aiding in enforcing health policies related to smoking and mitigating associated health risks effectively.
For instance, Google Cloud leverages image processing technology for smoker detection. The Google Cloud Vision API detects text in images, which can be adapted to recognize smoker indicators. This enhances health monitoring by ensuring more accurate and efficient data management using Cloud Storage for data storage and Cloud Functions for automated monitoring processes. Google Cloud thus facilitates effective health monitoring through these integrated services[3].

In conclusion, technological innovations like visual detection systems and cloud services play a crucial role in combating the public health impacts of smoking. They provide advanced tools for monitoring and enforcing health regulations, ultimately contributing to a healthier environment for all.

2. RESEARCH METHOD

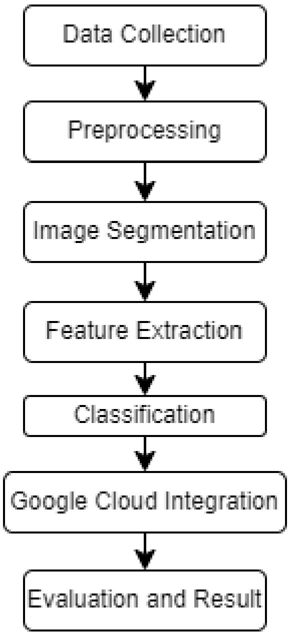

Figure 1. Thinking Framework Picture

Smoker detection using Google Cloud services and infrastructure involves a segmentation process to identify relevant areas of images, followed by feature extraction to distinguish the presence of smoking behavior. Classification algorithms use machine learning models to predict image classes as smoker or non-smoker. Services like AutoML Vision or Cloud Vision API accelerate this process by providing pre-trained classification algorithms or enabling custom model training. Integrating image processing methods with Google Cloud allows rapid and efficient processing of large-scale image data, supporting public health monitoring and innovative technological solutions for complex health issues[4].

2.1. Dataset

The dataset used consists of images downloaded from the Kaggle platform, specifically curated for image analysis and detection. It comprises a total of 600 images, with 250 training images depicting smokers and 250 non-smokers, along with 100 test images—50 each of smokers and non-smokers. The

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dataset includes diverse images of smokers, coughing individuals, people using inhalers, talking on the phone, and drinking. Researchers aimed to ensure diversity in both classes to enhance model training by inducing a certain level of class confusion. Varied conditions and positions in the images can bolster the analytical capabilities on Google Cloud.

According to Zha [5], the primary goal of this dataset is to develop and test a smoker detection model. The training data is utilized to train machine learning or artificial intelligence models, while the test data is used to evaluate the model's performance post-training. The dataset is split into 80% for training and 20% for testing. This dataset serves the purpose of developing and evaluating smoker detection models effectively. The following is an example of an image of a person smoking from Kaggle.

Figure 2. Smoker Images from Kaggle

2.2. Image Segmentation

The image segmentation process employs the K-means clustering algorithm, which divides an image into several segments based on color and texture similarities. This algorithm clusters pixels that share similar characteristics, forming homogeneous segments. To evaluate the quality of the segmentation, we use the Intersection over Union (IoU) metric, which measures the overlap between the predicted segmentation and the ground truth. Additionally, the Dice coefficient is used to assess the similarity between two samples, effectively evaluating the true positive rate of the segmentation.

2.3. Feature Extraction

During the feature extraction stage, techniques such as Scale-Invariant Feature Transform (SIFT) and Histogram of Oriented Gradients (HOG) are used to extract significant features from the segmented images. SIFT is employed to detect and describe local features in the images, while HOG identifies the orientation of gradients or edges within the images. This process also includes edge detection using the Canny method to identify significant edges, as well as texture analysis to evaluate texture patterns in the images. These techniques aim to identify unique characteristics that can distinguish between smokers and non-smokers.

2.4. Classification

Once the features are extracted, the next step involves classification using Support Vector Machine (SVM) and Neural Networks. SVM is utilized to find the optimal hyperplane that separates the smoker and non-smoker classes in the feature space, while neural networks provide a more complex and deep approach to data classification. The performance of the classification models is evaluated using various metrics, including accuracy, which measures the proportion of correctly classified instances out of the total instances. Precision evaluates the ratio of true positive predictions to the total positive predictions, recall measures the ratio of true positive predictions to the actual positive instances, and the F1 score, which is the harmonic mean of precision and recall, provides a single metric to evaluate the overall performance of the model.

2.5. Image Processing on Google Cloud

Image processing on Google Cloud involves uploading images to Google Cloud Storage, where they can be preprocessed for quality and format. The Cloud Vision API then analyzes these images, performing tasks like object detection, text extraction, and facial recognition. Advanced users can utilize

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machine learning tools such as AutoML Vision or custom TensorFlow models for specialized image classification and analysis. Results can be integrated with other Google Cloud services for scalable and efficient data processing, making it a versatile platform for a wide range of image-related tasks from basic analysis to sophisticated machine learning applications[6][7].

2.6. Image Data Analysis Testing

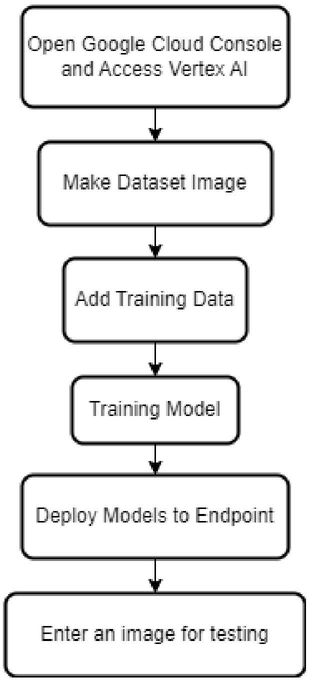

Figure 3. Workflow of the Smoker Detection

The technical explanation for using Google Cloud for image analysis to detect smokers begins with the initial step of open a web browser and navigate to the Google Cloud console at console.cloud.google.com then click on the search menu and type and select "Vertex AI".Creating a dataset begins by selecting the "Create a dataset" option at the bottom. Choose "Image" as the dataset type since the researcher is working with images. Next, provide a relevant name for the dataset. For image classification, select single label because the object being studied has only one label, which is smoking or non-smoking. After successfully creating the dataset, the next step is to access it by clicking on the name of the newly created dataset. Training data can then be added by clicking the "Select File" button. Researchers can upload relevant training images for the analysis project. Ensure to provide appropriate labels for each image so that the model can learn the correct class or category of each image. This process ensures that your dataset is ready for training an image classification model. After finishing adding training data to the dataset, the next step is to train the model. Click the "Start Training" button to initiate this process. Researchers will be given the option to either create a new model from scratch or use an existing one. Next, select the training configuration that suits your project needs, such as the algorithm to be used, hyperparameters, and allocation of computing resources. This process will train the model based on the prepared data, enabling researchers to produce a model ready for image classification. After the model training process is complete, the next step is to return to the model dashboard. Select the trained model by clicking on it, then click the "Deploy Model" option. Researchers will be directed to the configuration page to deploy the model. At this stage, researchers can specify endpoint configurations, including location, endpoint name, and the resources to be used. Once the configuration is set up, click the "Deploy" button to initiate the model deployment process. By following these steps, researchers will successfully deploy the model, making it accessible through the created endpoint. Final steps click "Upload Image" and upload the test image data to evaluate the model's accuracy. After that, the results will appear.

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3. RESULTS AND DISCUSSION

This chapter will discuss the results of the research and testing that has been conducted. The Testing involves conducting Smoker Detection using Google Cloud Services and Infrastructure.

3.1. Impact of Cloud Computing on Image Processing

Cloud computing offers significant advantages for image processing tasks. Scalability allows users to adjust computing resources as needed, enhancing efficiency for intensive analyses. Cloud services provide robust infrastructure, significantly boosting image processing speeds. High availability ensures uninterrupted access, crucial for continuous or real-time image processing applications. Cloud computing facilitates seamless team collaboration and provides monitoring tools for efficient image processing workflows[8].

While cloud computing has revolutionized image processing, challenges exist. Bandwidth limitations can slow down data transfer between users and the cloud, potentially delaying overall processing. Security risks include data leakage or theft during image data transfer or storage in the cloud, despite providers offering multiple security layers[9]. Issues with cloud computing resource availability may disrupt image processing, impacting real-time applications [10].

3.2. Detailed Evaluation

All labels

Average precision	0.995
Precision	96%
Recall	96%
Created	Apr 2, 2024, 9:21:25 AM
Total images	500
Training images	400
Validation images	50
Test images	50

Figure 4. Detail Evaluation

Figure 4 shows a precision result of 96%, indicating that the majority of cases predicted as positive by the model are indeed positive. In the context of smoker detection, this high precision demonstrates the model's ability to accurately identify images containing smokers[11]. A recall of 96% indicates the model's capability to retrieve most of the actual smoker cases present in the dataset. The model tends to miss very few actual smoker cases. According to Lestari[12], high precision and recall rates suggest that the model performs well with minimal false positives and a low number of missed smoker cases.

3.3 Precision-recall Threshold

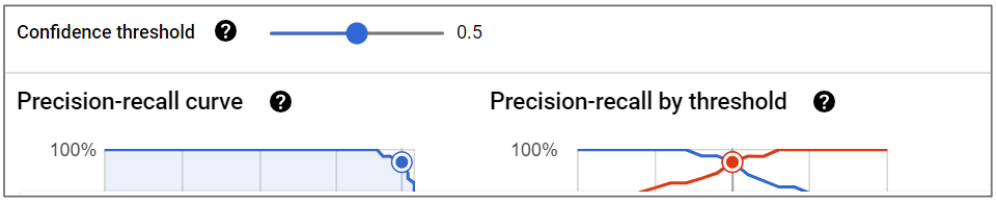

Figure 5. Precision-Recall and Threshold

Figure 5 displays the Precision-Recall (PR) curve, a useful visualization tool for evaluating classification model performance, particularly in scenarios where minority classes or positive cases are rare. The PR curve illustrates the relationship between precision and recall at various threshold values used by the model to classify instances. Precision measures the proportion of correctly predicted positives out of all predicted positives, while recall measures the proportion of correctly predicted positives out of all actual positive instances [13].A Precision-Recall Curve at 100% and a Precision-Recall Threshold also at 100% can refer to two distinct situations. A Precision-Recall Curve at 100%

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may indicate that the model achieves 100% precision across all observed recall ranges on the PR curve. This signifies that the model provides completely accurate positive predictions for all detected positive cases, without any false positive results. A Precision-Recall Threshold at 100% indicates that the threshold used by the model to classify instances as positive or negative has been set to 100%. The model will only make positive predictions if it is completely confident that the instance is truly positive. While this can result in high precision, it may also reduce recall as some actual positive cases might be missed[14]. Both a Precision-Recall Curve at 100% and a Precision-Recall Threshold at 100% indicate excellent model performance in classifying positive cases, with perfect precision.

3.4 Confusion matrix of label predictions

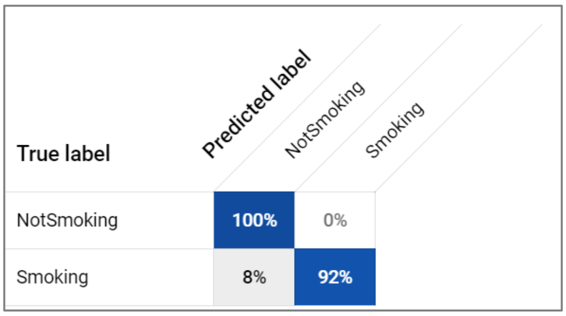

Figure 6. Confusion matrix of label predictions

Figure 6 illustrates a confusion matrix. In the first scenario, the model accurately predicts the "notsmoking" label with 100% precision. This means all predictions made by the model for "notsmoking" are correct. However, despite the high precision of 100% for "notsmoking" predictions, there is a small portion (8%) of cases that should have been "notsmoking" but were incorrectly predicted as "smoking”. In the second scenario, the model does not make any predictions for the "smoking" label in cases that should be "notsmoking". This results in a 0% precision for "smoking" predictions in "notsmoking" cases. However, when the model predicts the "smoking" label in cases that are actually "smoking", it achieves a precision of 92%. This indicates that 92% of all "smoking" predictions are correct.Overall, these results show that the model performs well in identifying the "notsmoking" class with high precision but makes some errors in predicting "smoking" in cases that should be "notsmoking". On the other hand, the model has high precision in predicting "smoking" when the class occurs, while not making "smoking" predictions for cases that should be "notsmoking".

3.5 Confusion matrix calculates label predictions

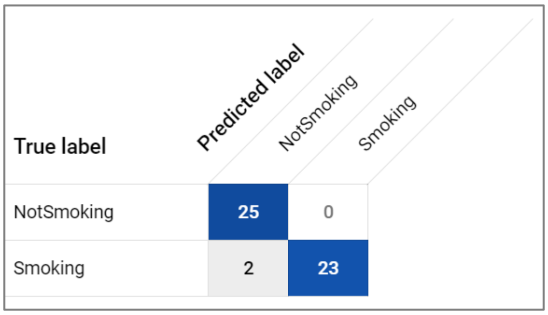

Figure 7. Confusion matrix calculates label predictions

Figure 7 depicts the model predicting the "notsmoking" label, with 25 correct predictions. This means that most of the cases that should be "notsmoking" were correctly predicted as "notsmoking". However, despite the high precision of 100% for "notsmoking" predictions, there are 2 cases that were incorrectly predicted as "smoking" out of the total number of "notsmoking" predictions. In the second situation, the model does not make any "smoking" predictions for cases that should be "notsmoking", resulting in all "smoking" predictions in "notsmoking" cases being correct negatives. However, when the model predicts the "smoking" label, it correctly predicts 23 cases. Overall, the model demonstrates a high level of precision in predicting the "notsmoking" label, with 100% correct predictions. However,

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there are some errors in predicting "smoking" in cases that should be "notsmoking". On the other hand, the model does not make "smoking" predictions at all for cases that should be "notsmoking" and shows good precision in predicting "smoking" in cases that should be "smoking".

3.6 Accurate predictions of non-smokers and smokers in the test images

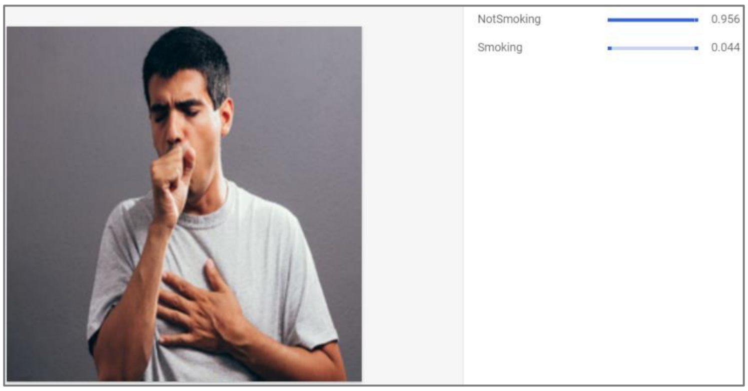

Figure 8. Correct Prediction of Non-Smokers

This figure demonstrates the machine learning model's capability to accurately identify non-smokers. The individuals shown are coughing, and the model successfully distinguishes this as a non-smoking activity. This accurate prediction showcases the model's effectiveness in differentiating between smoking and non-smoking actions based on subtle cues.

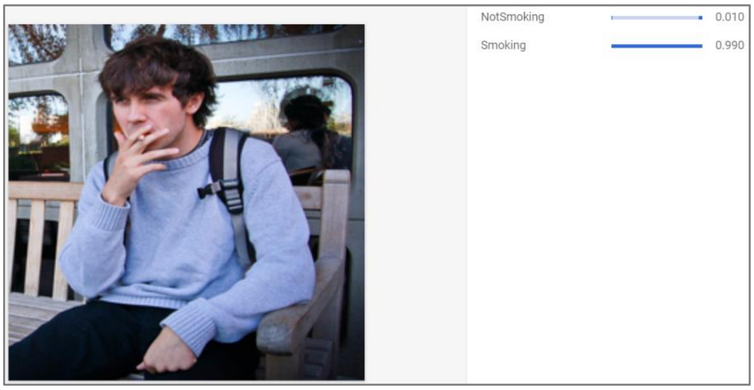

Figure 9. Correct Prediction of Smokers

Figure 9 illustrates the model's precision in identifying smokers. The individuals using cigarettes are correctly labeled as smokers. This accuracy highlights the model's ability to detect smoking activities, leveraging visual cues associated with cigarette usage to make correct predictions.

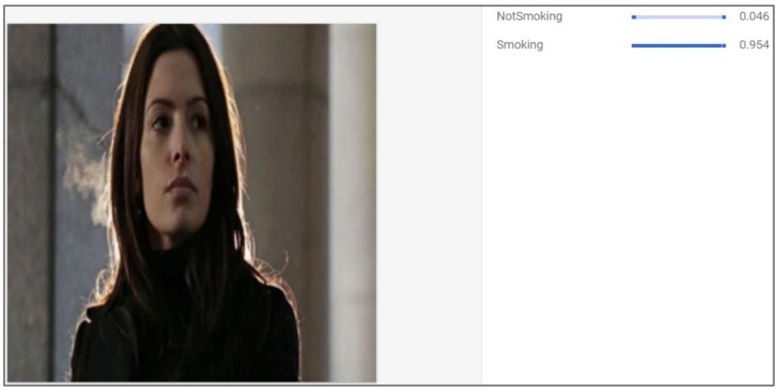

Figure 10. Incorrect Prediction Due to Mistaken Cues

Figure 10 presents an example of a misprediction by the model. The image contains mist that resembles cigarette smoke due to cold air, or a woman's hair that might be detected as cigarette smoke.

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These elements cause the model to incorrectly identify the situation as smoking, emphasizing the challenges in distinguishing between similar visual patterns.

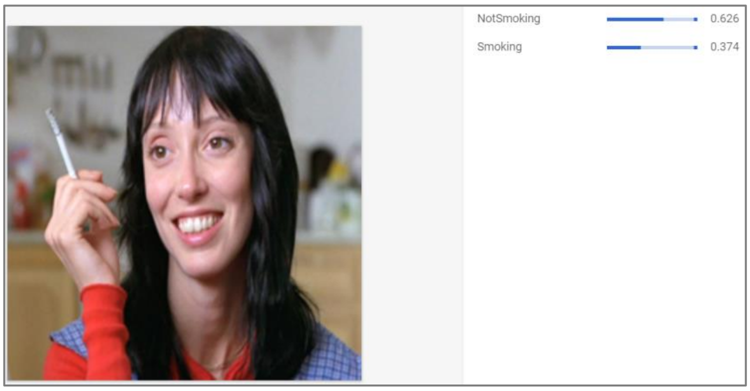

Figure 11. Incorrect Prediction Due to Unclear Cigarette Image

Figure 11 shows another instance of misprediction. The image contains an unclear object that resembles a cigarette, such as a pen, and lacks smoke. This ambiguity leads the model to fail in detecting the cigarette image accurately. This example highlights the limitations of the model when dealing with unclear or ambiguous visual inputs.

4. CONCLUSION

Cloud computing offers significant advantages for image processing tasks. Scalability allows users to adjust computing resources as needed, enhancing efficiency for intensive analyses. Cloud services provide robust infrastructure, significantly boosting image processing speeds. High availability ensures uninterrupted access, crucial for continuous or real-time image processing applications. Cloud computing facilitates seamless team collaboration and provides monitoring tools for efficient image processing workflows [15].

While cloud computing has revolutionized image processing, challenges exist. Bandwidth limitations can slow down data transfer between users and the cloud, potentially delaying overall processing. Security risks include data leakage or theft during image data transfer or storage in the cloud, despite providers offering multiple security layers. Issues with cloud computing resource availability may disrupt image processing, impacting real-time applications.

REFERENCES

[1] Fariz Kahendra, Bagoes Widjanarko, dan Farid Agushybana, "Faktor-Faktor yang Mempengaruhi Implementasi Kebijakan Kawasan Tanpa Rokok : Literature Review," *Media Publ. Promosi Kesehat. Indones.*, vol. 6, no. 3, hal. 430–435, 2023, doi: 10.56338/mppki.v6i3.3284.

[2] M. I. Gojali dan E. L. Tjiong, "Pengembangan Aplikasi Deteksi Objek Rokok Dan Kegiatan Merokok Menggunakan Algoritma YOLOv3," *KALBISCIENTIA J. Sains dan Teknol.*, vol. 10, no. 02, hal. 201–208, 2023, doi: 10.53008/kalbiscientia.v10i02.3108.

[3] P. Baker dan L. Collins, "Creating and analysing a multimodal corpus of news texts with Google Cloud Vision's automatic image tagger," *Appl. Corpus Linguist.*, vol. 3, no. 1, hal. 100043, 2023, doi: 10.1016/j.acorp.2023.100043.

[4] J. Valentino dan Y. A. Susetyo, "Analisis Perbandingan Optical Character Recognition Google Vision dengan Microsoft Computer Vision pada Pembacaan KTP-el," *J. JTIK (Jurnal Teknol. Inf. dan Komunikasi)*, vol. 7, no. 4, hal. 552–561, 2023, doi: 10.35870/jtik.v7i4.1046.

[5] D. Zha, Z. P. Bhat, K. H. Lai, F. Yang, dan X. Hu, "Data-centric AI: Perspectives and Challenges," *2023 SIAM Int. Conf. Data Mining, SDM 2023*, hal. 945–948, 2023, doi: 10.1137/1.9781611977653.ch106.

[6] A. Ravikumar dan H. Sriraman, "Acceleration of image processing and computer vision

Volume 11, Issue 2, October 2024, pp. 135-142
ISSN 2355-5068 ; e-ISSN 2622-4852
DOI: 10.33019/jurnalecotipe.v11i2.4499

algorithms," *Handb. Res. Comput. Vis. Image Process. Deep Learn. Era*, hal. 1–18, 2022, doi: 10.4018/978-1-7998-8892-5.ch001.

[7] A. Amrullah, A. Nugroho, dan Z. Ramadhan, "Perbandingan Kinerja Web Server Pada Penyedia Layanan Cloud Microsoft Azure Dan Amazon Web Services," *J. Inform. Teknol. dan Sains*, vol. 5, no. 1, hal. 92–97, 2023, doi: 10.51401/jinteks.v5i1.2487.

[8] M. I. P. Nasution, "TEKNIK PELESTARIAN PRIVASI DATA DI DATABASE CLOUD Raisida Salwa, Muhammad Irwan Padli Nasution Fakultas Ekonomi Dan Bisnis Islam Universitas Islam Negeri Sumatera Utara," vol. 3, no. 7, 2024.

[9] Ferryanto dan N. Chandra, "Analisis Ancaman Keamanan Data Dalam Cloud Computing," *JCOME (Journal Comput. Multimed. Enginering)*, vol. 1, hal. 1–5, 2023.

[10] B. R. Allo, N. Mardiana, O. Soleh, dan V. Lazinu, "Peran Teknologi Cloud Computing Dalam Transformasi Infrastruktur Ti Perusahaan: Studi Analisis Implementasi Di Industri Manufaktur," *J. Cahaya Mandalika*, vol. 18, hal. 1408–1414, 2018.

[11] F. R. Tarigan, R. Andrian, dan R. Safe'i, "Klasifikasi Skala Kerapatan dan Transparansi Tajuk Jenis Daun Jarum dengan VGG16," *MALCOM Indones. J. Mach. Learn. Comput. Sci.*, vol. 3, no. 2, hal. 253–263, 2023, doi: 10.57152/malcom.v3i2.940.

[12] F. Lestari, E. D. Putra, A. Sonita, dan Y. Darnita, "Human Object Counter Tracking Using Connected Component Labelling On Digital Image Processing," *J. Komputer, Inf. dan Teknol.*, vol. 3, no. 2, hal. 251–258, 2023, doi: 10.53697/jkomitek.v3i2.1218.

[13] R. F. Putra dan D. I. Mulyana, "Optimasi Deteksi Objek Dengan Segmentasi dan Data Augmentasi Pada Hewan Siput Beracun Menggunakan Algoritma You Only Look Once (YOLO)," *J. JTIK (Jurnal Teknol. Inf. dan Komunikasi)*, vol. 8, no. 1, hal. 93–103, 2024, doi: 10.35870/jtik.v8i1.1391.

[14] J. Alfred Daniel, C. Chandru Vignesh, B. A. Muthu, R. Senthil Kumar, C. B. Sivaparthipan, dan C. E. M. Marin, "Fully convolutional neural networks for LIDAR–camera fusion for pedestrian detection in autonomous vehicle," *Multimed. Tools Appl.*, vol. 82, no. 16, hal. 25107–25130, 2023, doi: 10.1007/s11042-023-14417-x.

[15] D. He dan S. Xiong, "Image Processing Design and Algorithm Research Based on Cloud Computing," *J. Sensors*, vol. 2021, 2021, doi: 10.1155/2021/9198884.