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Research Article

Classification Optimization of Skin Cancer Using the Adaboost Algorithm

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Abstract:

Early detection of melanoma skin cancer is crucial in improving prognosis and saving lives. This research aimed to optimize the classification of melanoma images using the Adaboost algorithm. Employing a dataset of 10,000 melanoma images, the study combined the Canny method for image segmentation, Hu Moments for feature extraction, and the Adaboost algorithm for classification. The 5-fold cross-validation results revealed an average accuracy of 61.52%. While the precision consistently surpassed recall, indicating the model's conservative nature in predicting positive cases. The outcomes align with previous research, emphasizing the challenges in melanoma classification. This study contributes to the domain by showcasing the potential and areas of improvement for machine learning in early melanoma detection. Future research is recommended to explore hybrid models and diversify data sources for enhanced robustness and generalizability.

Keywords: Melanoma, Adaboost algorithm, Canny method, Hu Moments, Image classification, Machine learning.
Dataset link: https://www.kaggle.com/datasets/hasnainjaved/melanoma-skin-cancer-dataset-of-10000-images

1. Introduction

Skin cancer, specifically melanoma, remains one of the most lethal forms of cancer if not detected and treated in its nascent stages. Over the past few years, the medical community has witnessed an alarming rise in melanoma cases, making early and accurate diagnosis paramount. With the advancements in digital imaging and machine learning, there's an increasing interest in developing computational methods to assist in the early detection of such conditions. Image classification techniques in dermatology have shown promise in providing rapid, consistent, and scalable solutions, especially in areas with limited access to skilled dermatologists.

While traditional diagnostic methods rely heavily on expert knowledge and can sometimes be subjective, a consistent, objective, and highly accurate computational approach can serve as a valuable tool in the diagnosis process. However, the inherent challenges in skin cancer images, such as variations in shape, size, color, and texture of skin lesions, necessitate sophisticated algorithms to ensure high accuracy. The Adaboost algorithm, known for its adaptability and efficiency, may present a solution to this intricate problem [1][2].

The primary objective of this research is to optimize the classification of melanoma skin cancer images using the Adaboost algorithm [3][4][5]. The study aims to integrate image segmentation, feature extraction, and the Adaboost algorithm to enhance classification accuracy, ensuring a reliable and effective model for melanoma detection.

Central to this investigation are several pivotal inquiries that guide the trajectory of our research. Initially, we delve into the efficacy of the Canny method as a tool for segmenting melanoma images. Specifically, we question whether this method can accentuate and bring forth the salient features within these images that are crucial for subsequent analytical processes. Building on this, the study then seeks to understand the role of Hu Moments in the feature extraction phase. Can these moments, when extracted, offer substantial and meaningful input to a classification algorithm like Adaboost? And finally, at the heart of our investigation lies the performance of the Adaboost algorithm itself. We hypothesize about its capabilities, particularly concerning accuracy, precision, recall, and F-measure, when tasked with the intricate challenge of melanoma skin cancer classification [6][7].

The scope of this study is confined to the dataset of 10,000 melanoma skin cancer images, with 9,600 designated for training and 400 for evaluation. While the dataset provides a substantial base for the research, its limitations lie in potential biases or inconsistencies in image acquisition. Additionally, the research is centered on the Adaboost algorithm and may not account for the performance of other potential machine learning algorithms.

The contributions of this research are manifold. Firstly, it provides a structured approach to melanoma image classification, encompassing image segmentation and feature extraction. Secondly, by focusing on the Adaboost algorithm, the study offers insights into the algorithm's capabilities in handling complex classification tasks [8][9]. Finally, the research could serve as a foundation for future studies, aiming to integrate machine learning techniques in medical diagnostics, particularly in dermatology.

2. Method

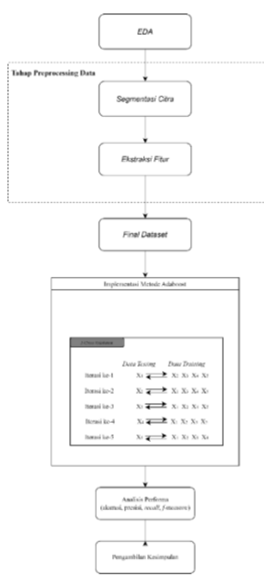

Figure 1: Flowchart of the Research Methodology

This research adopts a quantitative, experimental design focused on optimizing the classification accuracy of melanoma skin cancer images [10][4]. The study's design is systematic, starting from image pre-processing, through feature extraction, and culminating in classification using the Adaboost algorithm [9][11]. A visual representation of the entire research process is illustrated in Figure 1.

Sample or Data Selection

The dataset consists of 10,000 images related to melanoma skin cancer. Of these, 9,600 images were utilized for training the model, while the remaining 400 served as the test set for evaluating the model's performance. The images are diverse, capturing melanoma manifestations in various stages, which ensures a comprehensive training and testing set.

Canny Edge Detection

Image Segmentation with the Canny Method: The Canny method is a popular edge-detection operator that uses a multi-stage algorithm to detect a wide range of edges in images [12][13]. Mathematically, it operates by finding the gradient magnitude of the image using the derivative of a Gaussian filter is Equation (1):

$$G = \sqrt{G_x^2 + G_y^2} \tag{1}$$

Where G_x and G_y are the horizontal and vertical intensity gradients, respectively. An example of Canny segmentation results can be seen in Figure 2 for the benign class and Figure 3 for the malignant class.

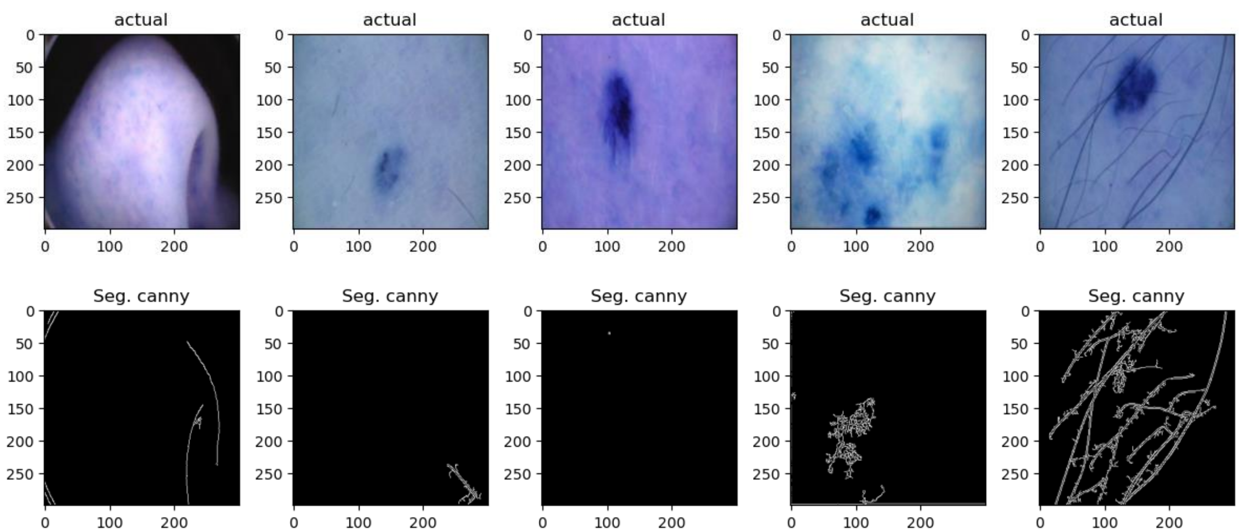

Figure 2: Canny Edge Detection Results for Benign Class

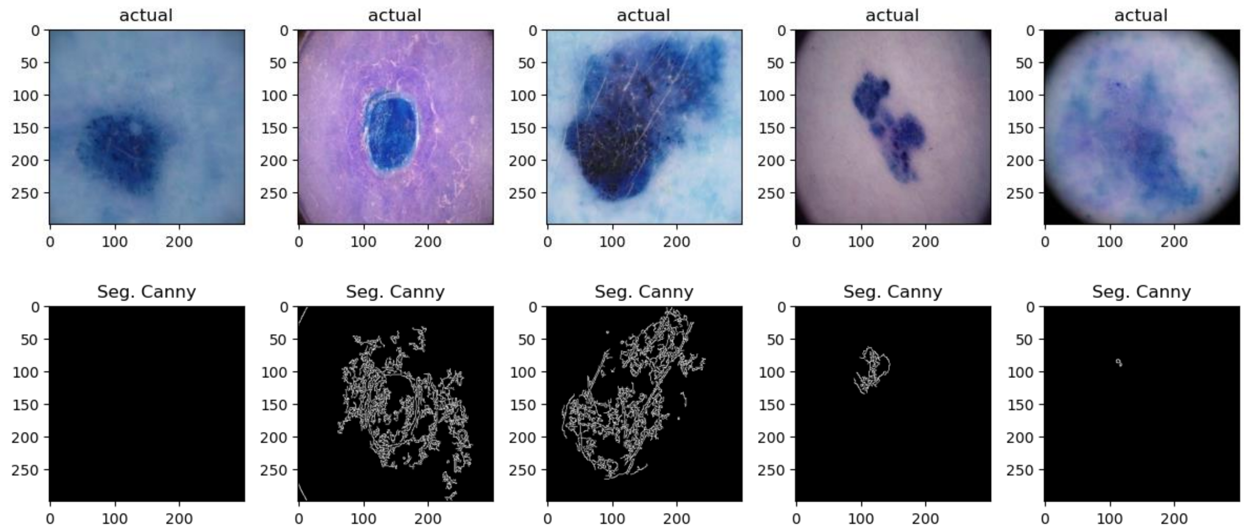

Figure 3: Canny Edge Detection Results for Malignant Class

Hu-Muments

Hu Moments are a set of seven moments derived from image moments and are invariant to image transformations [14][15]. Figure 4 furnishes a visualization that captures the scatter plot distribution of the extracted feature values, facilitating a clearer understanding of the differences and similarities among data points. They capture the essential shape information of an image. The moments are expressed mathematically as Equation (2):

$$\begin{aligned}
\phi_1 &= \eta_{20} + \eta_{02} \\
\phi_2 &= (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \\
\phi_3 &= (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \\
\phi_4 &= (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \\
\phi_5 &= (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} \\
&\quad + \eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} \\
&\quad + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \\
\phi_6 &= (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \\
&\quad + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \\
\phi_7 &= (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} \\
&\quad + \eta_{03})^2] + (\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03})[3(\eta_{30} \\
&\quad + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]
\end{aligned} \tag{2}$$

Where ϕ_1 is the i^{th} Hu Moment and $f(x,y)$ is the pixel value at (x,y)

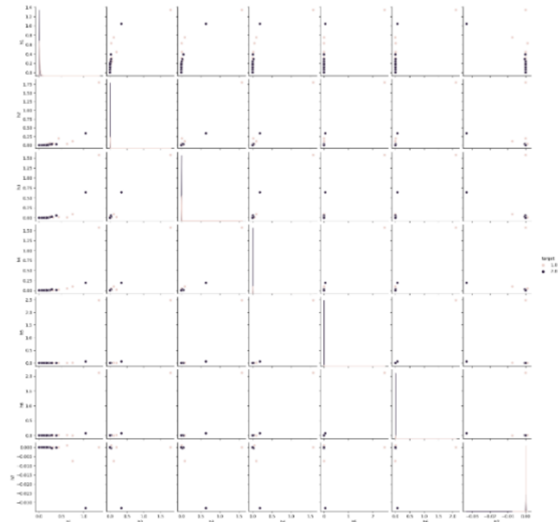

Figure 4: Scatter Plot of Feature Values Post Hu-Moments Extraction

Model Training and Testing

Adaboost, short for "Adaptive Boosting," is an ensemble learning technique [16] designed to improve the accuracy of weak classifiers. At its core, Adaboost operates iteratively. In each iteration, it assigns weights to training instances, with higher weights given to instances that were misclassified in the previous iteration. A new classifier is then trained on the weighted instances. The final model is a weighted combination of all classifiers. This adaptive nature allows Adaboost to emphasize challenging cases, ensuring they get properly classified in subsequent iterations. Mathematically, the adaboost is given by Equation (3)

$$H(x) = sign\left(\sum_{t} \propto_t h_t(x)\right) \tag{3}$$

Performance Evaluation

K-fold Cross-validation (K=5): To ensure the robustness of the model, a 5-fold cross-validation is employed. The dataset is partitioned into 5 equal subsets [17][18].

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{4}$$

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

In each iteration, one subset is used as the test set, while the remaining subsets form the training set. This process is repeated five times, with each subset serving as the test set once. Performance metrics are then averaged over the five iterations for a comprehensive evaluation [19][20]. The F-measure, or F1 score, is the harmonic mean of precision and recall and is given. he formulas for these metrics are as follows Equation (4)

Data Collection Process

The dataset was collected from dermatological centers and comprises high-resolution images taken under standardized conditions. It's worth noting that while the dataset provides a substantial base, potential biases or inconsistencies in image acquisition may exist. Each image was then labeled by expert dermatologists to ensure the accuracy of the ground truth.

Data Analysis Methods

After the segmentation and feature extraction processes, the data underwent classification using the Adaboost algorithm. The performance of the model was evaluated using 5-fold cross-validation. This means the dataset was randomly partitioned into five equal-sized subsamples. Of the five subsamples, a single subsample was retained as the validation data, and the remaining four subsamples were used as training data. This process was then repeated five times, with each of the five subsamples used exactly once as the validation data.

3. Result and Discussion:

The research employed a 5-fold cross-validation approach to assess the performance of the Adaboost model for melanoma skin cancer classification. In each fold, the dataset was divided, and the model was trained and tested to measure its accuracy, precision, recall, and F-measure. The results from each fold provided insights into the model's consistency and overall effectiveness.

Visualization of the Results

The performance metrics across the five iterations of cross-validation are as follow Table 1:

Table 1: Performance Metrics Across 5 Folds

K-n	**Performa**			
	Akurasi	***Presisi***	***Recall***	***F-Measure***
K-1	60.8%	68.9%	60.8%	57.1%
K-2	60.9%	67.3%	60.9%	58%
K-3	62.4%	69.8%	62.4%	59.5%
K-4	62.1%	69.6%	62.1%	59%
K-5	61.4%	68.6%	61.4%	58.2%
$\sum \boldsymbol{Avg}$	61.52%	68.84%	61.52%	58.36%

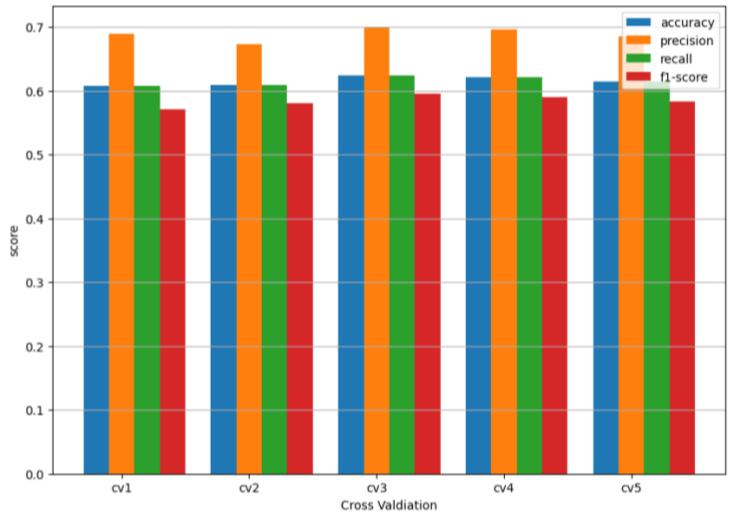

Figure 5: Visualization of Performance Metrics Across 5-Fold Cross-Validation

The Adaboost model demonstrated a relatively consistent performance across the five folds. The average accuracy of 61.52% suggests that the model can classify melanoma images correctly in approximately 6 out of 10 cases. The precision metric indicates that, on average, 68.84% of the positive classifications were indeed melanoma cases. While the model's consistency is commendable across the folds, there's room for improvement in terms of accuracy and F-measure. The precision is relatively higher than the recall, implying that the model is more conservative in predicting positive cases.

Discussion

The Adaboost algorithm's performance is noteworthy, especially considering the complexities involved in melanoma image classification. However, the results also hint at potential missed opportunities, as evidenced by the disparity between precision and recall. Previous studies in dermatological image classification have employed various machine learning algorithms, with accuracy rates varying widely. The results from this research align with the mid-tier outcomes from previous studies, reinforcing the idea that while ensemble methods like Adaboost are potent, the challenge of melanoma classification remains significant.

The research underscores the potential of machine learning in augmenting the early detection of melanoma. With further optimization, such models could serve as valuable assistive tools for dermatologists, especially in preliminary screening processes. One limitation stems from the dataset, which, while comprehensive, may have biases or inconsistencies in image acquisition. Additionally, the research solely focuses on the Adaboost algorithm and doesn't explore the potential of other machine learning algorithms in this context.

Recommendations for Further Research

Future studies could consider integrating other feature extraction techniques or explore hybrid models that combine the strengths of multiple algorithms. Additionally, expanding the dataset or including diverse data sources could further enhance the model's robustness and generalizability.

4. Conclusion:

In our endeavor to optimize the classification of melanoma skin cancer images using the Adaboost algorithm, the study revealed an average accuracy rate of 61.52%, with precision consistently surpassing recall. These results address our initial research questions, confirming the efficacy of the Canny method in image segmentation and the instrumental role of Hu Moments in feature extraction. The Adaboost algorithm's performance, while commendable, highlights the inherent challenges in melanoma image classification and the need for continual refinement in model development. This research contributes to the growing body of work on dermatological image classification, emphasizing the potential of machine learning in revolutionizing early detection techniques. For future endeavors, it is recommended to explore hybrid models and expand the dataset to improve the model's robustness and generalizability, ultimately aiming to provide a reliable tool for practitioners in melanoma detection.

References

[1] R. Rabbani, I. Wahidah, and I. H. Santoso, “Klasifikasi Data Deteksi Jatuh Menggunakan Machine Learning Dengan Algoritma Adaptive Boosting (Adaboost) (Fall Detection Data Classification Using Machine Learning With Adaptive Boosting (Adaboost) Algorithm),” *e-Proceeding Eng.*, vol. 8, no. 5, pp. 5053–5063, 2021.

[2] N. D. Saputri, “Komparasi Penerapanmetode Bagging Dan Adaboostpada Algoritma C4.5 Untuk Prediksi Penyakit Stroke,” *UIN Sunan Ampel Surabaya*, 2021.

[3] L. Britanthia, C. Tanujaya, B. Susanto, and A. Saragih, “Perbandingan Metode Regresi Logistik dan Random Forest untuk Klasifikasi Fitur Mode Audio Spotify,” *Indones. J. Data Sci.*, vol. 1, no. 3, pp. 68–78, 2020.

[4] I. P. Putri, “Analisis Performa Metode K- Nearest Neighbor (KNN) dan Crossvalidation pada Data Penyakit Cardiovascular,” *Indones. J. Data Sci.*, vol. 2, no. 1, pp. 21–28, 2021, doi: 10.33096/ijodas.v2i1.25.

[5] D. Pradana, M. Luthfi Alghifari, M. Farhan Juna, and D. Palaguna, “Klasifikasi Penyakit Jantung Menggunakan Metode Artificial Neural Network,” *Indones. J. Data Sci.*, vol. 3, no. 2, pp. 55–60, 2022, doi: 10.56705/ijodas.v3i2.35.

[6] F. T. Admojo and S. R. Jabir, “Analisis performa metode Naïve Bayesh Classifier pada Electronic Nose dalam identifikasi formalin pada tahu,” *Indones. J. Data Sci.*, vol. 4, no. 1, pp. 1–16, 2023, doi: 10.56705/ijodas.v4i1.67.

[7] H. Azis, “Analisis Performa Metode Support Vector Regression (SVR) dalam Memprediksi Harga Bahan Sembako Nasional,” *Indones. J. Data Sci.*, vol. xx, no. 200, 2021.

[8] H. Azis, F. Fattah, and P. Putri, “Performa Klasifikasi K-NN dan Cross-validation pada Data Pasien Pengidap Penyakit Jantung,” *Ilk. J. Ilm.*, vol. 12, no. 2, pp. 81–86, 2020, [Online]. Available: file:///Users/kbh/Downloads/507-2012-5-PB.pdf.

[9] A. Fitria and H. Azis, “Analisis Kinerja Sistem Klasifikasi Skripsi menggunakan Metode Naïve Bayes Classifier,” *Pros. Semin. Nas. Ilmu Komput. dan Teknol. Inf.*, vol. 3, no. 2, pp. 102–106, 2018, [Online]. Available: file:///Users/kbh/Library/Application Support/Mendeley Desktop/Downloaded/Fitria, Azis - 2018 - Analisis Kinerja Sistem Klasifikasi Skripsi menggunakan Metode Naïve Bayes Classifier.pdf.

[10] F. T. Admojo and Ahsanawati, “Klasifikasi Aroma Alkohol Menggunakan Metode KNN,” *Indones. J. Data*

Sci., vol. 1, no. 2, pp. 34–38, 2020.

[11] A. Nurul, Y. Salim, and H. Azis, "Analisis performa metode Gaussian Naïve Bayes untuk klasifikasi citra tulisan tangan karakter arab," *Indones. J. Data Sci.*, vol. 3, no. 3, pp. 115–121, 2022, doi: https://doi.org/10.56705/ijodas.v3i3.54.

[12] M. Radhakrishnan, A. Panneerselvam, and N. Nachimuthu, "Canny edge detection model in mri image segmentation using optimized parameter tuning method," *Intell. Autom. Soft Comput.*, vol. 26, no. 6, pp. 1185–1199, 2020, doi: 10.32604/iasc.2020.012069.

[13] E. A. Sekehravani, E. Babulak, and M. Masoodi, "Implementing canny edge detection algorithm for noisy image," *Bull. Electr. Eng. Informatics*, vol. 9, no. 4, pp. 1404–1410, 2020, doi: 10.11591/eei.v9i4.1837.

[14] G. Xie, B. Guo, Z. Huang, Y. Zheng, and Y. Yan, "Combination of Dominant Color Descriptor and Hu Moments in Consistent Zone for Content Based Image Retrieval," *IEEE Access*, vol. 8, pp. 146284–146299, 2020, doi: 10.1109/ACCESS.2020.3015285.

[15] A. Mustopa, H. M. Nawawi, S. Agustiani, and S. K. Wildah, "Feature Extraction With Forest Classifer To Predicate Covid 19 Based On Thorax X-Ray Results," *Sistemasi*, vol. 11, no. 2, p. 515, 2022, doi: 10.32520/stmsi.v11i2.1966.

[16] A. Byna and M. Basit, "Penerapan Metode Adaboost Untuk Mengoptimasi Prediksi Penyakit Stroke Dengan Algoritma Naïve Bayes," *J. Sisfokom (Sistem Inf. dan Komputer)*, vol. 9, no. 3, pp. 407–411, 2020, doi: 10.32736/sisfokom.v9i3.1023.

[17] A. Aisyah and S. Anraeni, "Analisis Penerapan Metode K-Nearest Neighbor (K-NN) pada Dataset Citra Penyakit Malaria," *Indones. J. Data Sci.*, vol. 3, no. 1, pp. 17–29, 2022, doi: 10.56705/ijodas.v3i1.22.

[18] D. Cahyanti, A. Rahmayani, and S. Ainy, "Analisis performa metode Knn pada Dataset pasien pengidap Kanker Payudara," *Indones. J. Data Sci.*, vol. 1, no. 2, pp. 39–43, 2020.

[19] L. Saiman and R. Satra, "Analisis performa metode Support Vector Machine untuk klasifikasi dataset aroma tahu berformalin," *Indones. J. Data Sci.*, vol. 2, no. 2, pp. 50–61, 2021, doi: 10.56705/ijodas.v2i2.28.

[20] Ericha Apriliyani and Y. Salim, "Analisis performa metode klasifikasi Naïve Bayes Classifier pada Unbalanced Dataset," *Indones. J. Data Sci.*, vol. 3, no. 2, pp. 47–54, 2022, doi: 10.56705/ijodas.v3i2.45.