Journal of Intelligent System and Telecommunications

Journal homepage: https://journal.unesa.ac.id/index.php/jistel/index

Cat Breed Classification Based on Ear and Facial Features Using K-Nearest Neighbors

Miftahus Sholihin[1*], *Syahrul Firmansyah*[2], *Moh. Rosidi Zamroni*[3], *M. Ghofar Rohman*[4]

[1,2,3,4]Informatics Engineering, Universitas Islam Lamongan, Indonesia
[1]Faculty of Computer Sciences and Information Technology, University Tun Hussein Onn Malaysia, Malaysia
*Correspondence: E-mail: miftahus.sholihin@unisla.ac.id

ARTICLE INFO

Article History:
Submitted/Received 22 April 2025
First Revised 21 Mei 2025
Accepted 26 Mei 2025
First Available Online 11 June 2025
Publication Date 11 June 2025

Keyword:
Classification, Features, Identifying, K-Nearest Neighbors, Recognition.

ABSTRACT

Identifying cat breeds is often challenging, mainly due to the similarity of physical features between breeds and the high frequency of crossbreeding. This study aims to develop a cat breed classification system based on facial features, especially ear shape and facial structure, using the K-Nearest Neighbors (K-NN) algorithm. Five cat breeds—Bengal, British Shorthair, Mainecoon, Persian, and Sphynx—were used as test objects with 50 test data. The evaluation results show that the K value dramatically affects the system's accuracy, with the highest accuracy of 90% achieved at K values = 4, 5, and 7. The Bengal breed showed the highest classification accuracy of 100%, while the Sphynx breed performed the lowest in several scenarios. These findings confirm that facial features are relevant and effective parameters in cat breed identification and that the K-NN method can be a lightweight yet accurate classification solution. This study contributes to developing an image recognition system based on specific visual features for pet classification.

1. INTRODUCTION

Cats are one of the most popular pets in the world, with a vast population and breed diversity[1], [2]. However, purebred cats only make up about 1% of the total cat population, with the remainder consisting of domestic or mixed-breed cats[3], [4], [5], [6]. This diversity, coupled with the high crossbreed rate between breeds, often makes it difficult for owners and practitioners to identify cat breeds[7] accurately. Each cat breed has distinctive morphological characteristics, such as body shape, fur texture and color, and facial and ear structure. However, in practice, identifying breeds based on these characteristics is not always easy to do visually, especially by the general public. Misperceptions often occur, such as considering all cats with thick fur as Angora or Persian breeds[1]. This complexity requires an accurate, reliable, and easy-to-use breed identification system.

Along with the advancement of technology in the era of artificial intelligence (AI), image recognition methods have become a promising approach in visual object classification, including pet breed identification. Various approaches have been developed, from conventional classification to deep learning-based approaches. One relatively simple but effective classification method is K-Nearest Neighbors (K-NN). Several previous studies have shown that K-NN can achieve a high level of accuracy in cat breed classification, with results reaching up to 94% accuracy based on six physical attributes[3]. However, most of these studies still focus on general features such as body shape and fur length, while more distinctive facial features have not been explored in depth.

Facial features—especially ear shape and facial contour—have great potential as parameters for differentiating between breeds. Therefore, this study aims to develop a cat breed classification system based on the K-NN method, primarily focusing on facial and ear features. This approach enriches scientific studies in pattern recognition and visual classification and contributes to developing a more precise and practical breed identification system.

This study is expected to produce a more accurate, efficient, and applicable classification model by integrating the K-NN method and utilizing more specific facial features. The results of this study can provide real benefits for cat owners, breeders, and cat lover communities in recognizing and understanding the characteristics of each breed more objectively and based on data.

2. METHODS

The system developed in this study consists of several main stages, as shown in **Figure 1**. The first stage is image acquisition, where the system receives input images to be further processed. The images used are images of cats, with 150 images, consisting of 100 images for training data and 50 for testing data.

The next stage is preprocessing, which aims to prepare the image to be suitable for the feature extraction process. At this stage, the image is converted to grayscale format, and image size normalization is performed to standardize the input dimensions.

After that, the system performs feature extraction by combining two methods: Histogram of Oriented Gradients (HOG) and Gray Level Co-occurrence Matrix (GLCM). HOG is used to capture information about the shape or contour of objects in the image, while GLCM is used to extract texture features from the image. The results of these two extraction methods are then combined into one feature vector.

DOI: https://doi.org/10.26740/jistel.v1n2.p151-161
e- ISSN 3090-613X

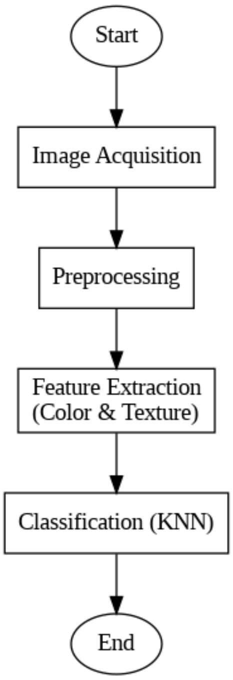

Figure 1. Overall System Flow Diagram.

The final stage is classification using the K-Nearest Neighbor (KNN) algorithm. This algorithm determines the class of the input image based on the closest distance to the labeled training data. The classification process is done by finding the value of k nearest neighbors based on the Euclidean distance of the input image feature vector to the training data.

To clarify the system's input and output components, the input to the system is a preprocessed grayscale image of a cat, which is transformed into a numerical feature vector through the combination of HOG and GLCM feature extraction. These feature vectors serve as the input for the classification process. The output of the system is a predicted class label that represents the breed of the cat. In this study, the classification is limited to five predefined clusters, corresponding to five distinct cat breeds: Bengal, British Shorthair, Mainecoon, Persian, and Sphynx. Thus, the system performs a multiclass classification task with five output categories. The prediction is made using the K-Nearest Neighbor algorithm, which assigns a class based on the majority class among the k nearest training samples in the feature space.

2.1. Image Acquisition

The initial stage in this research begins with the image acquisition process, namely, taking pictures of cat objects as the primary data. All images used were obtained directly from the cat lover community in the Lamongan area, East Java. The images were taken in natural conditions without artificial backgrounds to represent more realistic image variations in the actual environment. The device used for image capture is the Redmi Note 11 cellphone camera, which has a primary camera capability of 50 MP, sufficient to produce sharp and clear image quality. All images are saved in JPEG format and at their original resolution before the pre-processing stage.

The total number of images successfully collected and used in this study was 150 in five different breeds: Bengal, British Shorthair (BSH), Mainecoon, Persian, and Sphynx. Each class consists of 30 images, so that the dataset is balanced. For the purposes of training and system evaluation, the dataset is divided into two parts, namely 100 images used as training data and 50 images as testing data. This division, with a ratio of 2:1, is intended to provide sufficient data in the training process while allowing for a representative evaluation of classification performance. The training data is used to build a classification model using the K-Nearest

Neighbors (K-NN) algorithm, while the testing data is used to measure the accuracy of the system built.

2.2 Preprocessing

Image preprocessing is an essential initial stage in a digital image processing system to improve image quality and prepare it for the feature extraction stage. In this study, the images obtained from the acquisition process were first converted from RGB color format to grayscale. This process aims to simplify visual data without eliminating important information related to texture and shape, which are the basis for feature extraction.

In addition to color conversion, an image size normalization process is also carried out to equalize the dimensions of all images to be processed and minimize differences in spatial attributes between data. The image size is 256 × 256 pixels to balance detailed representation and computational efficiency. This pre-processing process is carried out consistently on training and test data to maintain the uniformity of input data at the feature extraction stage.

2.3 Feature Extraction

After going through the pre-processing stage, the cat image, converted into grayscale format and normalized in size, is processed at the feature extraction stage. This stage aims to obtain a numerical image representation as a feature vector containing important information, such as shape and texture, for classification. In this study, feature extraction was done by combining two methods: Histogram of Oriented Gradients (HOG) and Gray Level Co-occurrence Matrix (GLCM).

The extraction results from these two methods are then combined (concatenated) into one combined feature vector representing each cat image in shape and texture. This vector is used as input in the classification stage.

2.3.1 Histogram of Oriented Gradients (HOG)

In this study, the Histogram of Oriented Gradients (HOG) method is used as one of the techniques in the feature extraction process because of its ability to capture the shape and structure of the object's edge effectively[8], [9], [10]. The HOG process begins with converting the input image into grayscale format to simplify the gradient calculation without reducing crucial structural information.

Next, horizontal (Gx) and vertical (Gy) gradients are calculated using derivative operators to detect changes in pixel intensity. These results calculate the gradient magnitude and orientation for each pixel. The image is then divided into small cells (e.g., 8×8 pixels), and at each cell a gradient orientation histogram is calculated, where each bin represents a certain angle and is weighted based on the gradient magnitude.

To improve the robustness to lighting and contrast variations, some cells are grouped into blocks (e.g., 2×2 cells), and the histogram of each block is normalized. This normalization process improves the reliability of the descriptor under different lighting conditions. Finally, all the normalized histograms from all the blocks are combined into a single HOG feature vector representing the structural patterns in the image and used as input in the classification stage as shown in **Figure 2**.

DOI: https://doi.org/10.26740/jistel.v1n2.p151-161
e- ISSN 3090-613X

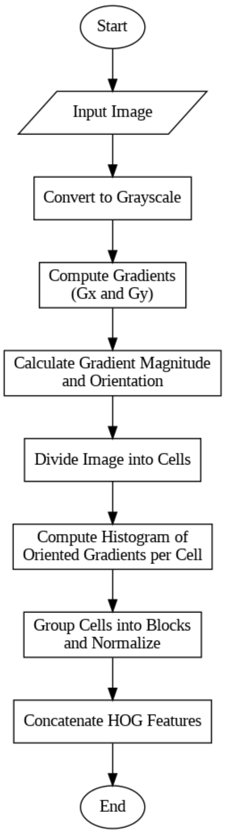

Figure 2. Feature Extraction Process Using HOG.

2.3.2 Gray Level Co-occurrence Matrix (GLCM)

A feature extraction process is carried out using the Gray Level Co-occurrence Matrix (GLCM) method to obtain texture information from the image[11] shown in **Figure 3**. This process begins by entering the image as input. The initial step is to convert the image from RGB format to grayscale, because GLCM works at the gray intensity level, representing the variation in the gray level of pixels in the image.

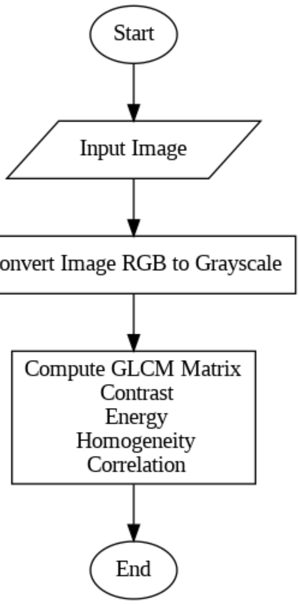

Figure 3. Texture Feature Extraction Process with GLCM**[12]**.

DOI: https://doi.org/10.26740/jistel.v1n2.p151-161
e- ISSN 3090-613X

After the image is converted to grayscale, the GLCM matrix is calculated, representing the frequency of occurrence of a particular pair of pixel intensity values with a certain distance and direction. This matrix extracts several main texture statistical features: contrast, energy, homogeneity, and correlation[13], which are calculated by Eq. (1), (2), (3), and (4), respectively.

$$\text{Contrast} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(i-j)^2 * P(i,j) \tag{1}$$

$$\text{Energy} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}P(i,j)^2 \tag{2}$$

$$\text{Homogeneity} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\frac{P(i,j)}{1+|i-j|} \tag{3}$$

$$\text{Correlation} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\frac{(i-\mu_i)(j-\mu_j)P(i,j)}{\sigma_i\sigma_j} \tag{4}$$

These features provide a representative picture of the texture of an image. For example, contrast indicates the level of intensity difference between pixels, energy indicates the uniformity of the pattern, homogeneity reflects the similarity of adjacent pixel values, and correlation measures the extent to which pixels are linearly related to each other. The resulting features are then used as input in the classification process.

2.4 K-Nearest Neighbor (KNN)

After the feature extraction process is completed using the Histogram of Oriented Gradients (HOG) and Gray Level Co-occurrence Matrix (GLCM) method, the next step is to classify the image data using the K-Nearest Neighbor (K-NN) algorithm, as shown in **Figure 4**. K-NN was chosen because of its simplicity in implementation and effectiveness in handling distance-based classification problems.

The classification begins by loading the extracted feature data from the training and test data. The parameter value k, representing the nearest neighbors, is determined first, as this value will significantly affect the classification performance. Furthermore, the Euclidean distance is calculated against all training data for each test data point to measure the closeness between features[14], [15], [16], [17]. The distance between a test sample x and a training sample x_i with n features is computed using the Euclidean distance formula, as shown in Eq. (5).

$$D(x,y) = \sqrt{\sum_{j=1}^{n}(x_i - x_{ij})^2} \tag{5}$$

After calculating the distance, all training data are sorted by the closest distance to the test data. Then, the k closest training data (nearest neighbors) are selected to be used as the basis for making classification decisions. The class of the test data is determined based on the most common classes from the k nearest neighbors. Thus, each test data point can be classified into the most appropriate class based on features similar to the existing training data.

DOI: https://doi.org/10.26740/jistel.v1n2.p151-161
e- ISSN 3090-613X

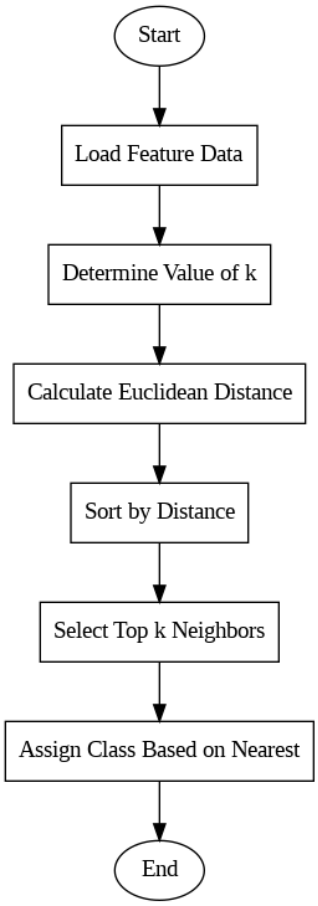

Figure 4. Classification Process with KNN.

3. RESULTS AND DISCUSSION
3.1. Results

Figure 5 shows the classification accuracy results of five cat breeds against variations in the K value in the K-Nearest Neighbor (KNN) algorithm, with each class having 10 test data. Each accuracy value displayed represents the percentage of test images successfully classified correctly. The Bengal breed showed the most stable classification performance with 100% accuracy consistently across all K values from 1 to 10, meaning that all 10 test images were always classified correctly regardless of the variation in the K value. This shows that the visual features of Bengal are powerful and distinctive, making them easily distinguishable by the system.

In contrast, the Sphynx breed shows the most significant fluctuation. At K = 1, its accuracy reaches 60%, then drops drastically to 40% at K = 2, meaning only 4 out of 10 images are correctly recognized. After that, its performance increases gradually, namely 70% at K = 3, 80% at K = 4, 5, 6, and 9, then peaks at K = 7 with 90% accuracy, before dropping again to 70% at K = 8 and 60% at K = 10. This variation indicates that the visual features of the Sphynx tend to be less contrasty or similar to other breeds, making it difficult for the model to perform stable classification.

The British Shorthair (BSH) breed also shows fluctuations, although not as extreme as the Sphynx. Its accuracy is at its lowest at K = 1 at 60%, then increases to 70% at K = 2 and 3, and peaks at K = 4 at 90%. After that, the accuracy drops slightly to 80% at K = 5 and 6, then drops

DOI: https://doi.org/10.26740/jistel.v1n2.p151-161
e- ISSN 3090-613X

back to 70% at K = 7 to K = 10. This shows that the system is quite sensitive in classifying BSH, and the accuracy depends on selecting the correct K value.

The Mainecoon breed performed quite stably with an accuracy of 90% at K = 1, then dropped to 80% at K = 2, 3, and 4. Then, its performance reached a maximum point of 100% at K = 5, 6, and 7, maintaining a high accuracy of 90% at K = 8 and 9, before finally dropping to 70% at K = 10. This indicates that the K value in the range of 5–7 is the best configuration for distinguishing the Mainecoon breed.

The Persian breed shows consistent performance with an accuracy of 80% at K = 1 and 2, increasing to 100% at K = 3, dropping slightly to 90% at K = 4, and then rising back to 100% at K = 5. After that, Persian maintains an accuracy of 90% at K = 6 to K = 10. These results indicate that the system can recognize the Persian breed well and stably, although there is still a slight decrease at low K values.

Overall, the figures in the graph show that the K value significantly impacts the classification's stability and accuracy. The values of K = 4, 5, and 7 generally produce the highest accuracy and a relatively even distribution between classes, so they can be considered optimal values. The explanation of each point in this graph reinforces the understanding that accuracy is not just a statistical number, but also reflects how well the visual features of each race can be represented and distinguished by the facial feature-based classification system.

These results show that the K value significantly affects the classification performance. K values = 4, 5, and 7 provide the best results with high accuracy and relatively balanced distribution between classes, so they can be considered optimal values for the dataset and features used. Conversely, K values that are too small (e.g., K = 1) or too large (K = 10) tend to produce less stable performance on some classes[18].

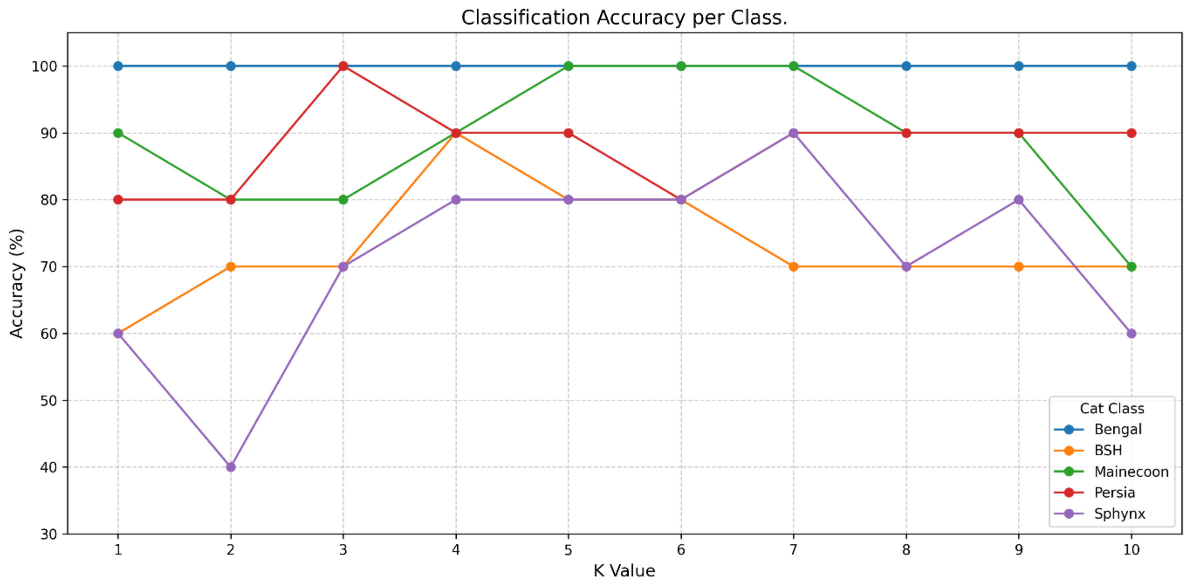

Figure 5. KNN Classification Accuracy Graph per Class.

3.2. Discussion

The results of the cat breed classification experiment using the K-Nearest Neighbor (KNN) algorithm with a combination of HOG and GLCM features show that the selection of the K value significantly affects the model performance. Consistently, the values of K = 4, 5, and 7 provide the highest accuracy of 90%, while K values that are too small (K = 1, 2) or too large (K = 10) produce less stable performance. This finding aligns with the basic principle of KNN, where too few neighbors are susceptible to outliers, while too many can lead to over-generalization and loss of local details.

Regarding class, the Bengal breed achieved the highest performance, with 100% accuracy at all K values. This indicates that the shape and texture features of the Bengal breed are quite distinctive and easy to recognize, even in a simple classification scenario such as KNN. In contrast, the Sphynx breed showed relatively high accuracy variability, even reaching a low of 40% at K = 2. This phenomenon can be explained by the high visual similarity between the Sphynx and some other breeds, especially due to the plain skin texture and minimal fur details, which make the features from HOG and GLCM less able to provide sharp discrimination.

Classes such as British Shorthair (BSH) and Persian also show fluctuating accuracy. This indicates that although the features used can capture the general shape and texture structure, there are some cases of visual ambiguity between breeds that require exploration of additional features, such as coat color or other morphological traits, which are not fully covered by the combination of HOG and GLCM.

The results of this study showed a maximum accuracy of 90%, comparable to previous research[3], which used the K-NN method with six physical attributes and achieved an accuracy of 94%. This difference in accuracy can be explained by the differences in the features used. Previous research used a combination of body attributes such as fur length, color, and size, while this study only utilized facial features. In addition, the study only used two types of cats: the Angora and Kampung. Another study conducted by Rahmat[1] using the CNN method gave lower results with an accuracy of 77.62%. Meanwhile, when compared, the research conducted by Ramadhani[6], Prasetyo[7], and Mulyana[19] also gave higher results.

Compared to deep learning-based approaches, the KNN method has several advantages, including ease of implementation, computational efficiency, and ease of interpretation of results. This makes KNN a lightweight and practical alternative, especially for rapid identification systems implemented on devices with limited resources, such as mobile applications or animal adoption systems. However, the KNN model also has limitations, especially when dealing with data that has similar visual characteristics between classes. This can be seen in the classification results for the Sphynx breed, which experienced quite large fluctuations in accuracy due to the lack of contrasting visual characteristics on the face of this type of cat.

The facial feature-based approach proposed in this study is an effective solution for cat breed recognition, mainly when applied to frontal or close-up facial images. This approach is suitable for applications that emphasize speed, are lightweight in computation, and do not require a complex training process, making it potentially suitable to be adopted in developing image-based pet identification systems in the real world.

4. CONCLUSION

This study shows that the K-Nearest Neighbors (K-NN) method effectively classifies cat breeds based on facial features, especially ear shape and facial structure, with the highest accuracy reaching 90% at K values = 4, 5, and 7. These results indicate that facial features have significant potential as discriminatory parameters between breeds, with the highest performance achieved in the Bengal breed and the lowest performance in the Sphynx breed. This approach offers higher efficiency and specificity than previous studies that focused on general body features.

DOI: https://doi.org/10.26740/jistel.v1n2.p151-161
e- ISSN 3090-613X

However, the system's accuracy could be further improved by incorporating additional morphological features, such as fur color, pattern, or head proportions. Future work may explore the use of deep learning-based approaches, such as Convolutional Neural Networks (CNNs), which are capable of learning more complex and abstract features directly from raw images. Additionally, increasing the size and diversity of the dataset and experimenting with hybrid classification models could further enhance the system's robustness and generalization. This study provides a useful foundation for the development of accurate, lightweight, and practical cat breed identification systems applicable to mobile devices, veterinary use, and animal welfare platforms.

5. ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to the cat enthusiast community in Lamongan for their valuable support and contribution in providing image data for this research. This research was supported by the Faculty of Science and Technology, Universitas Islam Lamongan.

6. AUTHORS' NOTE

The authors declare that there is no conflict of interest regarding the publication of this article. The authors confirmed that the paper was free of plagiarism.

7. AUTHORS' CONTRIBUTION/ROLE

Miftahus Sholihin: conceptualized the study, designed the methodology, and supervised the research process; Syahrul Firmansyah: collected the data, performed the data analysis; Moh. Rosidi Zamroni: drafted the manuscript and handled the literature review; M. Ghofar Rohman: drafted the manuscript and handled the literature review.

8. REFERENCES

[1] G. Rahmat, M. I. H. Daffy, and E. Anggi, "Klasifikasi Jenis Ras Kucing Dengan Gambar Menggunakan Convolutional N eural Network (CNN)," *Jurnal interkom*, 2024, doi: 10.35969/interkom.v18i4.318.

[2] J. Kusuma, A. Jinan, M. Z. Lubis, R. Rubianto, and R. Rosnelly, "Komparasi Algoritma Support Vector Machine Dan Naive Bayes Pada Klasif ikasi Ras Kucing," *generic*, vol. 14, no. 1, pp. 8–12, Jan. 2022, doi: 10.18495/generic.v14i1.122.

[3] A. Wiwin, W. Reza, L. Yuni, I. B., A. W. Dibyo, and U. E., "Implementation of the K-Nearst Neighbor (k-NN) Algorithm in Classifica tion of Angora and Country Cats," *Journal of Applied Intelligent System*, 2023, doi: 10.33633/jais.v8i1.7129.

[4] N. Azahro Choirunisa, T. Karlita, and R. Asmara, "Deteksi Ras Kucing Menggunakan Compound Model Scaling Convolutional Ne ural Network," *TMJ*, vol. 6, no. 2, pp. 236–251, Nov. 2021, doi: 10.33050/tmj.v6i2.1704.

[5] Z. Gu, "Recognition of feline images based on deep learning," *Applied and Computational Engineering*, vol. 5, pp. 345–352, May 2023, doi: 10.54254/2755-2721/5/20230594.

[6] A. N. Ramadhayani and V. Lusiana, "KLASIFIKASI JENIS KUCING MENGGUNAKKAN ALGORITMA PRINCIPAL COMPONENT ANALYSIS DAN K-NEAREST NEIGHBOR," *Jurnal Informasi dan Komputer*, vol. 10, no. 2, pp. 257–263, Oct. 2022, doi: 10.35959/jik.v10i2.333.

[7] D. H. Prasetyo, W. K. D., and alif F. Farrady, "Identifikasi Jenis Ras Pada Kucing Menggunakan Algoritma Support Vecto r Machine (SVM)," *JASIEK (Jurnal Aplikasi Sains Informasi Elektronika dan Komputer)*, 2024, doi: 10.26905/jasiek.v6i1.10989.

[8] F. A. I. A. Putra, F. Utaminingrum, and W. F. Mahmudy, "HOG Feature Extraction and

KNN Classification for Detecting Vehicle in The Highway," *IJCCS (Indonesian Journal of Computing and Cybernetics Systems)*, vol. 14, no. 3, Art. no. 3, Jul. 2020, doi: 10.22146/ijccs.54050.

[9] L. Zhang, W. Zhou, J. Li, J. Li, and X. Lou, "Histogram of Oriented Gradients Feature Extraction Without Normalization," in *2020 IEEE Asia Pacific Conference on Circuits and Systems (APCCAS)*, Dec. 2020, pp. 252–255. doi: 10.1109/APCCAS50809.2020.9301715.

[10] K. Karthikeyan, A. V. Karpagam, and M. Manikandan, "Influence of binning in Histograms of Oriented Gradients method representation," in *2017 Fourth International Conference on Signal Processing, Communication and Networking (ICSCN)*, Mar. 2017, pp. 1–5. doi: 10.1109/ICSCN.2017.8085684.

[11] S. A. Rosiva Srg, M. Zarlis, and W. Wanayumini, "Identifikasi Citra Daun dengan GLCM (Gray Level Co-Occurence) dan K-NN (K-Nearest Neighbor)," *matrik*, vol. 21, no. 2, pp. 477–488, Mar. 2022, doi: 10.30812/matrik.v21i2.1572.

[12] M. Sholihin, S. Mujilahwati, and R. Wardhani, "CLASSIFICATION OF BATIK LAMONGAN BASED ON FEATURES OF COLOR, TEXTURE AND SHAPE," *Jurnal Ilmiah Kursor*, vol. 9, no. 1, Jul. 2017, doi: 10.28961/kursor.v9i1.114.

[13] I. S. Manuel and I. Ernawati, "Implementasi GLCM dan Algoritma Naive Bayes dalam Klasifikasi Jenis Bunga Anggrek," in *Prosiding Seminar Nasional Mahasiswa Bidang Ilmu Komputer dan Aplikasinya*, 2020, pp. 99–109. Accessed: Apr. 22, 2025. [Online]. Available: https://conference.upnvj.ac.id/index.php/senamika/article/view/638

[14] M. Sholihin and M. G. Rohman, "KLASIFIKASI KUALITAS MUTU TELUR AYAM RAS BERDASARKAN FITUR WARNA DAN TEKSTUR," *Jurnal teknika*, vol. 10, no. 2, Art. no. 2, Sep. 2018, doi: 10.30736/teknika.v10i2.244.

[15] M. Sholihin and M. G. Rohman, "Klasifikasi mutu telur berdasarkan fitur warna dengan menggunakan metode k-nearest neighbor," in *Seminar Nasional Sistem Informasi (SENASIF)*, 2018, pp. 1188–1193. Accessed: Dec. 17, 2024. [Online]. Available: https://jurnalfti.unmer.ac.id/index.php/senasif/article/download/181/150

[16] K. Marinatul, S. Luluk, and K. Siti, "Implementasi Algoritma K-Nearest Neighbor (K-NN) dalam Mengklasifikasi kan Berbagai Jenis Ekspresi Wajah Manusia," *Zeta - Math Journal*, 2024, doi: 10.31102/zeta.2024.9.1.10-20.

[17] M. Khaliqah, L. Sarifah, and S. Khotijah, "Implementasi Algoritma K-Nearest Neighbor (K-NN) dalam Mengklasifikasikan Berbagai Jenis Ekspresi Wajah Manusia," *Zeta - Math Journal*, vol. 9, no. 1, pp. 10–20, May 2024, doi: 10.31102/zeta.2024.9.1.10-20.

[18] P. Raktrakulthum and C. Netramai, "Vehicle classification in congested traffic based on 3D point cloud using SVM and KNN," in *2017 9th International Conference on Information Technology and Electrical Engineering (ICITEE)*, Oct. 2017, pp. 1–6. doi: 10.1109/ICITEED.2017.8250451.

[19] D. I. Mulyana and S. Nurhaliza, "Klasifikasi Jenis Kucing Menggunakan Algoritma K-Nearest Neighbor," *Jurnal JTIK (Jurnal Teknologi Informasi dan Komunikasi)*, vol. 9, no. 3, Art. no. 3, Mar. 2025, doi: 10.35870/jtik.v9i3.3821.

DOI: https://doi.org/10.26740/jistel.v1n2.p151-161
e- ISSN 3090-613X