# Evaluation of Various Error Metrics in K-NN Image Classification: A Case Study on Egg Image Processing

**Frainskoy Rio Naibaho*[1], Al-Khowarizmi[2]**
[1]Department of Information Technology, Institut Agama Kristen Negeri Tarutung
[2]Departement of Information Technology, Universitas Muhammadiyah Sumatera Utara Medan
e-mail: *[1]**frainskoy.rio.n@gmail.com**, [2]alkhowarizmi@umsu.ac.id

***Abstract***

*Image processing is a technique to create an image that appears and can be converted into light that describes 2 dimensions. The K-Nearest Neighbor (K-NN) algorithm is known for its efficiency and effectiveness in classification. Although K-NN is often used, a deep understanding of Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Deviation (MAD), especially in the context of image classification, still requires further exploration. This study aims to emphasize and measure the behavior of MSE, MAPE, and MAD when applied to K-NN classification results. In this study, statistical features such as mean, standard deviation, skewness, and kurtosis are extracted from the histogram of chicken egg images. These features are then normalized and used as input for the K-NN algorithm. Classification performance is evaluated using MSE, MAPE, and MAD. The results show that K-NN can classify chicken egg images with performance measured by MSE of 0.35114462, MAPE of 0.14237803%, and MAD of 0.52930142. The differences in these values, especially the much smaller MAPE value and in percentage units, underscore the importance of selecting the right metrics according to the needs of interpretation and practical applications. This study provides a clearer understanding of how different error metrics characterize the performance of K-NN in image classification, while also highlighting the need for comparative metric considerations in future research.*

***Keywords***— Image processing; Classification; K-NN; Various Error Metrics

## 1. INTRODUCTION

The development of technology today is very rapid, marked by the development of science and the emergence of new concepts in computing. The collection of knowledge will be computed to obtain classification or prediction, so that more accurate results are obtained and can be scientifically accounted for [1], [2], [3], [4]. The computer will read and interpret previously existing data automatically with the help of computing.

Image processing is a branch of computer science that studies images that are produced and then processed into information that can be understood by humans [5], [6], [7]. Images that represent original conditions have knowledge characteristics [8], [9]. Therefore, images that have information need to be classified so that they can be recognized in the computer process [10], [11]. On the other hand, various algorithms can be used in image processing to convey information from images through computer vision, which is used to explain data from various fields, such as manufacturing, medicine, education [12], agriculture, and others, as well as studying data from the past to produce useful information in the future. One example is a study conducted by Lubis et al. [14] to detect pests in tea leaves, which are an important source of protein for humans every day, by utilizing the Mamdani fuzzy method.

In daily activities, humans need protein, but to get the right protein, it is important to understand whether the protein is safe to consume [15]. Evaluation and analysis of the suitability of protein products are very important in order to provide new insights through data processing techniques [16]. Therefore, the use of computational methods is needed to carry out classification, so that humans do not feel hesitant when consuming protein.

Rahmadianto et al. [17] conducted a study using image processing on chicken eggs through the K-NN method and succeeded in achieving an accuracy of 86% in determining egg quality. In addition, Muzami et al. [18] also conducted a study to identify chicken egg images using the Region of Interest segmentation method, and succeeded in achieving an accuracy of 85% and an error rate of 15%. Dong et al [19] conducted a study by applying the Near-Infrared Hyper Spectral Imaging method to identify embryos contained in chicken egg images.

The procedure for detecting images requires a special classification method [20]. The classification process is one of the techniques in data mining used to identify new knowledge in data processing, so that it can be a basis for knowledge in accordance with the results of research that has been done, Indris, Salam, and Sunar [21] conducted a comparison between the classification of emotions carried out by Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) Neural Network, using prosody features and voice quality taken from the Berlin Emotional Database, as described. Thus, the classification process greatly supports learning activities on computers, where computer knowledge functions automatically [22], [23].

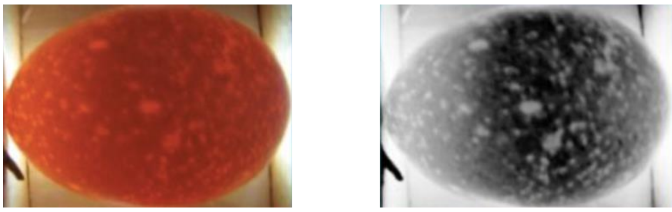
Recognition of images of reading the Al-Quran by using several distance formulas [24]. Meanwhile, [25] compares several accuracy techniques on the Random K-NN method with data on numerical data. The K-Nearest Neighbor (KNN) algorithm is the most frequently used among various machine learning algorithms [26], [27]. This paper requires image classification by applying the K-NN method to obtain optimal accuracy with several accuracy techniques.

## 2. RESEARCH METHODS

Presenting research sequentially, including research design, research steps (in algorithm format, pseudocode, or other forms), data collection, and testing method [5], [6], [7]. Explanations regarding the research process should be accompanied by references, so that the explanation can be accepted scientifically [6], [7], [9].

### *2.1. Dataset Process*

The dataset in this study uses chicken egg images taken with a smartphone camera. The eggs are illuminated using a special flashlight with 400 lumens indoors, with sufficient lighting conditions. The data used is primary data, collected by randomly collecting 30 chicken eggs. Then, a histogram analysis is carried out on the images that have been obtained to show the frequency of occurrence of each color gradation. The histogram of the image will be used to obtain the statistical characteristics of the image. To be clearer, the author will display the histogram in Figure 1 below.



(a) (b)

*Figure 1. Chicken egg dataset, (a) Original Image, (b) Grayscale Image*

Histogram analysis is performed on the image to show the frequency of occurrence of each color gradient. This image histogram is used to obtain the statistical characteristics of the image. The term "statistical approach" mentioned in the original manuscript refers to this feature extraction process, not as a separate classification method. A histogram is a graphical representation of the distribution of numerical data, showing how often each pixel value or range of pixel values occurs in the image. The goal of histogram adjustment is to obtain a balanced histogram distribution, so that each gray level has a relatively equal number of pixels. This process involves replacing the pixel gray values (r) with new gray values (s) through a transformation function T, where s = T(r). From this histogram, four main statistical features are extracted for each image: Mean (average pixel intensity), Standard Deviation (standard deviation of pixel intensity, a measure of contrast), Skewness (slope of the pixel distribution, a measure of asymmetry), and Kurtosis (peakness of the pixel distribution, a measure of the peak of the distribution). These features were chosen because they are able to capture important characteristics of the pixel intensity distribution in the image, which are relevant for classification.

### *2.2. General Architecture*

As for this paper, it is focused on the general architecture as depicted in Figure 2.

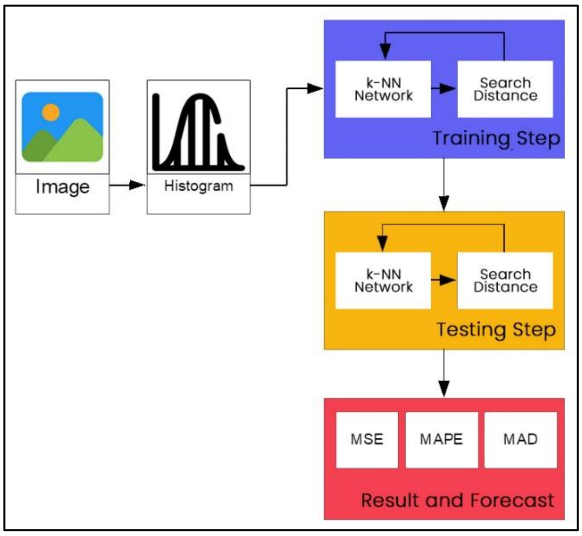



*Figure 2. General Architecture*

Explanation from step figure 2 as follows:

1. Do feature extraction on the chicken egg image.
2. Stage of conducting image training by getting the closest distance value
3. Perform the testing phase on the image by getting the closest distance value
4. Compute and compare several techniques for accuracy

MSE calculates the average of the squared differences between the actual and predicted values. This metric is very sensitive to large errors because the squaring process gives higher weight to larger deviations. Calculate the magnitude of the error using MSE with the following equation (1) [8], [28], [29], [30], [31], [32].

$$MSE = \frac{\sum_{t=1}^{n}(x-y)^2}{n} \quad (1)$$

MAPE measures the mean absolute error as a percentage. This metric provides a sense of the percentage error relative to the actual value, which is often more intuitive for interpretation. However, MAPE has limitations when the actual value ($x_t$) is close to or equal to zero, as it can lead to division by zero or very large values. Calculate the magnitude of the error using MAPE with the following equation (2) [33], [34], [35], [36].

$$MAPE = \frac{\sum_{t=1}^{n}\left|\frac{x-y}{x}\right|}{n} \times 100\% \quad (2)$$

MAD calculates the average of the absolute values of the differences between the actual and predicted values. This metric is more robust to outliers than MSE because it does not square the errors, so large errors do not dominate the calculation. Calculate the magnitude of the error using MAD with the following equation (3) [30], [31], [35], [36], [37], [38].

$$MAD = \frac{\sum_{t=1}^{n} |x-y|}{n} \tag{3}$$

Where in points (a), (b), and (c):
$x$ is actual data
$y$ is the result data
$n$ is lots of data.

## 3. RESULT AND DISCUSSION

At this stage, a chicken egg dataset was collected with a total of 30 eggs. The data set used is a primary dataset, collected by randomly collecting 30 chicken eggs. The eggs were obtained from egg sellers at random. The next step is to illuminate the eggs, using a special flashlight with 500 lumens. The results of the egg illumination were photographed using a smartphone camera for image processing. Then a histogram was made using the Python programming language tool. The syntax of the process of creating a histogram of chicken egg images can be seen in the following pseudocode.

```
import matplotlib.pyplot as plt
{
    x = [value1, value2, value3,....]
    plt.hist(x, bins = number of bins)
    plt.show()
}
```

*Figure 3. Pseudocode*

From the pseudocode above, accuracy evaluation is then carried out to be weighted in classifying with K-NN. This accuracy evaluation gets results and is used as a dataset in this paper. The accuracy evaluation is shown in Table 1.

*Table 1. Dataset With Accuracy Evaluation*

| Image ID | Mean | Deviation | Skewness | Kurtosis | y (Label) |
|---|---|---|---|---|---|
| Image 1 | 127.67209 | 62.44838 | 0.88080 | -1.02090 | 0 |
| Image 2 | 127.02724 | 58.07151 | 1.18357 | -0.45288 | 0 |
| Image 3 | 127.88343 | 58.29981 | 1.13858 | -0.54276 | 0 |
| Image 4 | 127.59362 | 55.71911 | 1.31979 | -0.12202 | 0 |
| Image 5 | 128.29472 | 55.92294 | 1.28038 | -0.22189 | 0 |
| Image 6 | 126.41798 | 55.28544 | 1.39079 | 0.05616 | 0 |
| Image 7 | 128.56388 | 56.01310 | 1.26654 | -0.25277 | 0 |
| Image 8 | 125.98834 | 57.78245 | 1.23705 | 0.33124 | 0 |
| Image 9 | 127.95849 | 60.49924 | 0.99349 | -0.82810 | 0 |
| Image 10 | 128.50983 | 60.65867 | 0.96124 | -0.87061 | 0 |
| Image 11 | 126.86113 | 62.38788 | 0.91384 | -0.96818 | 0 |
| Image 12 | 127.25764 | 62.94234 | 0.85001 | -0.98679 | 0 |
| Image 13 | 128.70540 | 60.56689 | 0.96218 | -0.88087 | 0 |
| Image 14 | 127.44094 | 62.45177 | 0.89161 | -1.00203 | 0 |
| Image 15 | 127.97960 | 60.48077 | 0.99357 | -0.82787 | 0 |
| Image 16 | 125.38986 | 39.82752 | 2.48565 | 5.34239 | 0 |
| Image 17 | 128.33419 | 41.85383 | 2.36807 | 3.68655 | 0 |
| Image 18 | 127.59856 | 46.51968 | 1.90049 | 2.17509 | 0 |
| Image 19 | 128.02436 | 49.76445 | 1.72416 | 1.06966 | 0 |
| Image 20 | 127.37735 | 40.85177 | 2.49623 | 4.29516 | 0 |

| | | | | | |
|---|---|---|---|---|---|
| Image 21 | 126.68173 | 52.34669 | 1.58129 | 0.60141 | 1 |
| Image 22 | 128.13597 | 55.89357 | 1.29070 | -0.19322 | 1 |
| Image 23 | 128.59943 | 56.01096 | 1.26228 | -0.26101 | 1 |
| Image 24 | 126.67942 | 58.00317 | 1.20136 | -0.41338 | 1 |
| Image 25 | 127.58920 | 55.70299 | 1.32221 | -0.12243 | 1 |
| Image 26 | 128.33419 | 41.85383 | 2.36807 | 3.68655 | 0 |
| Image 27 | 127.59856 | 46.51968 | 1.90049 | 2.17509 | 0 |
| Image 28 | 128.02436 | 49.76445 | 1.72416 | 1.06966 | 0 |
| Image 29 | 127.37735 | 40.85177 | 2.49623 | 4.29516 | 1 |
| Image 30 | 126.68173 | 52.34669 | 1.58129 | 0.60141 | 1 |

However, to make the data in Table 1 easy to classify, normalization is performed. After characterizing the features, data normalization is performed to ensure that all features have a uniform scale. Normalization is very important for distance-based algorithms such as K-NN because it prevents features with larger distance values from dominating the distance calculation. In this study, normalization is performed by changing the data range to between 0 and 1, using the maximum ($x_{max}$) and minimum ($x_{min}$) values of each feature. This technique is known as Min-Max normalization, and the formula is:

$$X_{normalized} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (4)$$

Where X is the original feature value, $X_{min}$ is the minimum value of the feature, and $X_{max}$ is the maximum value of the feature. After normalization, all data will be within the normal range. The visualization of the normalized data is shown in Figure 2.

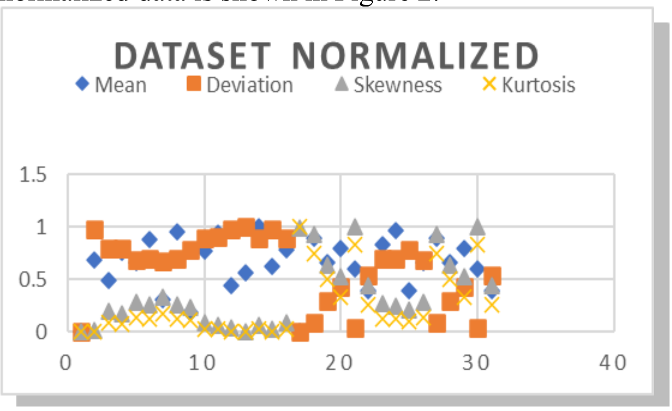



*Figure 4. Dataset Normalized*

From Figure 4, it can be seen that the statistical approach is used as a value or label in classification. In this paper, the classification process uses the K-NN method, where the K value is determined for learning by using the distance formula in finding the closest value. The results of the classification using K-NN are shown in Table 2 below.

*Table 2. Classification Result With KNN*

| Image ID | Classification with K-NN | Error MSE | Error MAPE | Error MAD |
|---|---|---|---|---|
| 1 | 0.57486223 | 0.33046658 | 0 | 0.574862230 |
| 2 | 0.33969394 | 0.11539198 | 0 | 0.339693940 |
| 3 | 0.34491429 | 0.11896586 | 0 | 0.344914290 |
| 4 | 0.16681664 | 0.02782779 | 0 | 0.166816640 |
| 5 | 0.29657649 | 0.08795761 | 0 | 0.296576490 |
| 6 | 0.36147999 | 0.13066779 | 0 | 0.361479990 |
| 7 | 0.36722431 | 0.13485369 | 0 | 0.367224310 |
| 8 | 0.54071557 | 0.29237333 | 0 | 0.540715570 |
| 9 | 0.47994305 | 0.23034533 | 0 | 0.479943050 |
| 10 | 0.56337498 | 0.31739136 | 0 | 0.563374980 |

| | | | | |
|---|---|---|---|---|
| 11 | 0.59386724 | 0.35267830 | 0 | 0.593867240 |
| 12 | 0.60349322 | 0.36420406 | 0 | 0.603493220 |
| 13 | 0.59417128 | 0.35303951 | 0 | 0.594171280 |
| 14 | 0.56944411 | 0.32426660 | 0 | 0.569444110 |
| 15 | 0.48108828 | 0.23144593 | 0 | 0.481088280 |
| 16 | 1.31561735 | 1.73084900 | 0 | 1.315617350 |
| 17 | 0.92744001 | 0.86014498 | 0 | 0.927440010 |
| 18 | 0.48152254 | 0.23186395 | 0 | 0.481522540 |
| 19 | 0.28660072 | 0.08213998 | 0 | 0.286600720 |
| 20 | 1.02329220 | 0.00054253 | 0.02329220 | 0.023292200 |
| 21 | 0.28036509 | 0.51787440 | 0.71963491 | 0.719634910 |
| 22 | 0.25700156 | 0.55204668 | 0.74299844 | 0.742998440 |
| 23 | 0.37746986 | 0.38754378 | 0.62253014 | 0.622530140 |
| 24 | 0.39108228 | 0.37078079 | 0.60891772 | 0.608917720 |
| 25 | 0.16566732 | 0.69611101 | 0.83433268 | 0.834332680 |
| 26 | 0.92744001 | 0.86014498 | 0 | 0.927440010 |
| 27 | 0.48152254 | 0.23186395 | 0 | 0.481522540 |
| 28 | 0.28660072 | 0.08213998 | 0 | 0.286600720 |
| 29 | 1.02329220 | 0.00054253 | 0 | 0.023292200 |
| 30 | 0.28036509 | 0.51787440 | 0.71963491 | 0.719634910 |

Table 2 shows the results of the classification with K-NN; however, following the focus of this paper, comparisons of several accuracy techniques are presented. Table 2 also shows the error values achieved by using MSE, MAPE, and MAD. Then, after proceeding to get the value of MSE errors, MAPE errors, and MAD errors. Accuracy calculations are carried out with formulas (1), (2), and (3), and the results are shown in Figure 4 below.

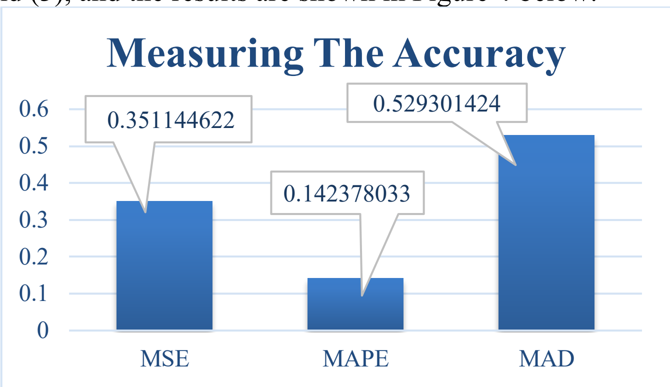



*Figure 5. Comparison of Several Accuracy Measurements*

From Figure 5, you can see the results in this paper by classifying the image of chicken eggs using the K-NN method and the statistical approach to achieve an MSE of 0.35114462; besides that, it is also calculated with a MAPE of 0.14237803% and finally, the calculation is carried out with an MAD of 0.52930142. It can be seen that MAPE gets a smaller value and has a percentage unit. Meanwhile, MSE and MAD do not involve percent (%), but the units are considered as units of MSE and units of MAD. MAPE (0.142%) shows a very small relative error. Since MAPE measures error as a percentage of the true value, this low value indicates that the K-NN prediction is relatively close to the true value. This is very useful in situations where understanding the error in terms of proportion or percentage is important, especially for parties that need a relatively easy-to-understand performance indicator.

## 4. CONCLUSION

This study successfully implemented the K-NN method for chicken egg image classification. The classification process involves image acquisition using a camera, histogram analysis to extract statistical features (mean, deviation, skewness, kurtosis), data normalization, and then classification using K-NN. To obtain a comprehensive understanding of the model performance, several accuracy measurement techniques, Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Deviation (MAD), were compared. The results showed that the K-NN model achieved competitive performance. The striking difference is that MAPE produces a very small value in percentage units, offering a different interpretation of relative error compared to MSE and MAD, which are absolute error metrics. This emphasizes that the selection of evaluation metrics must be adjusted to the needs of interpretation and practical application goals.

## 5. SUGGESTION

This study has several limitations. First, the dataset size used is relatively small, which is 30 chicken egg images, which may limit the generalizability of the findings. Second, this study only uses statistical features extracted from image histograms. The use of other features, such as texture, shape, or deep learning-based features, may produce different performance. Third, the focus of this study is on the evaluation of metrics for the K-NN algorithm; although comparisons with other algorithms have been added for context, a more in-depth study on a comprehensive comparison of algorithms is still needed. Based on these limitations, future research can be directed in several directions. It is recommended to conduct experiments on larger and more diverse datasets to validate the findings and improve the generalization of the model. In addition, exploration of more sophisticated feature extraction methods, including deep learning-based features (e.g., from Convolutional Neural Networks), can potentially improve classification accuracy. A comprehensive comparison of K-NN with other machine learning and deep learning algorithms (such as SVM, Random Forest, and Artificial Neural Networks) is also an important area for further research. Finally, further investigation into the optimal K-NN hyperparameter tuning (e.g., different K value selection methods and distance metrics) may provide additional insights.

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