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Comparison of Drone and Helicopter Image Classification Accuracy Using Naïve Bayes Based on Mean Red-Green-Blue (RGB) Values and First-Order Statistics

Astika Ayuningtyas [1, 2], Imam Riadi [3], Anton Yudhana [4]

Abstract

The increasing use of Unmanned Aerial Vehicles (UAVs) such as drones and helicopters across various sectors presents a challenge in distinguishing between them due to their similar appearances in aerial imagery. This similarity necessitates the development of an accurate image classification system to differentiate the two types of flying objects. This study proposes a classification method using the Naïve Bayes algorithm combined with two feature extraction approaches: (1) the mean intensity values of Red, Green, and Blue (RGB) image channels, and (2) first-order statistical features including mean, standard deviation, skewness, and kurtosis of pixel intensities. A dataset of 60 images, consisting of 30 drone and 30 helicopter images, was used. Feature extraction was conducted using Python in the Google Collab environment, while classification was performed with WEKA software. The results show that the RGB mean features yielded a classification accuracy of 91.67% with an area under the ROC curve (AUC) of 1.0, outperforming the statistical features, which achieved 75% accuracy and an AUC of 0.938. These findings demonstrate that colour-based RGB features are more effective in distinguishing drones from helicopters compared to statistical texture features.

Keywords:
Image Classification, Naïve Bayes, RGB, First-Order Statistics, Drone and Helicopter

1. Introduction

The development of Unmanned Aerial Vehicle (UAV) or drone and helicopter technologies has had a significant impact across various fields, such as area surveillance, search and rescue operations, and goods delivery [1]. In this context, aerial image classification systems play a critical role in a wide range of applications, including security monitoring, territorial mapping, and air traffic control. One of the main challenges in aerial image classification is distinguishing between different types of flying objects, such as drones and helicopters, which often exhibit similar visual characteristics—especially from certain angles or under varying lighting conditions. Differentiating these two types of objects requires a more refined approach to image processing to achieve high classification accuracy.

Pattern recognition based on image data provides an efficient solution to differentiate objects like drones and helicopters, considering their differences in color, texture, and shape [2]. In this regard, digital image classification techniques that utilize statistical

Corresponding Author: Astika Ayuningtyas (2437083006@webmail.uad.ac.id)
1 Astika Ayuningtyas, Informatika, Universitas Ahmad Dahlan, 2437083006@webmail.uad.ac.id
2 Astika Ayuningtyas, Informatika, Institut Teknologi Dirgantara Adisutjipto, astika@itda.ac.id
3 Imam Riadi, Sistem Informasi, Universitas Ahmad Dahlan, imam.riadi@is.uad.ac.id
4 Anton Yudhana, Teknikm Elektro, Universitas Ahmad Dahlan, eyudhana@ee.uad.ac.id

features—such as colour and texture information—are highly relevant. This study introduces a novel implementation of a conventional classification algorithm, Naïve Bayes, in the context of drone and helicopter differentiation. Although Naïve Bayes is widely regarded as a basic classifier, its application in this specific domain—distinguishing flying objects with high visual similarity—has not been extensively explored. The novelty of this research lies in demonstrating that, with well-chosen low-level features such as RGB mean values and first-order statistical descriptors, even a standard algorithm like Naïve Bayes can yield high classification performance. This supports the idea that efficient and interpretable methods can still be effective without the complexity of deep learning, especially in scenarios with limited data.

Naïve Bayes is selected due to its simplicity, low computational cost, and effectiveness in handling numerical data, making it particularly suitable for systems that require real-time processing or have resource constraints. While the algorithm assumes feature independence—an assumption not fully valid in image data—it often performs surprisingly well in practical applications, including image classification tasks [3]. In image classification, the extraction of colour and texture features is crucial. A commonly used approach involves extracting average values of Red, Green, and Blue (RGB) for colour features, while texture features can be derived using first-order statistical methods such as mean, standard deviation, skewness, and kurtosis of pixel intensity distributions [4], [5]. Despite their simplicity, these features are considered highly effective in representing the visual characteristics of objects in images and have been shown to improve classification accuracy in various studies.

Previous research has shown that combining colour features with first-order statistical features can enhance object classification performance in images [6]. For instance, in digital image processing studies [7], [8], the application of these techniques has proven effective in improving accuracy when distinguishing visually similar objects, such as drones and helicopters. Therefore, this study aims to compare the classification accuracy between drone and helicopter images using the Naïve Bayes method, based on features extracted from RGB mean values and first-order statistics. The results of this study are expected to contribute significantly to the development of computer vision-based flying object classification systems, using an efficient approach that is suitable for implementation in real-time and resource-constrained environments.

2. Related Works

The literature on the classification of aerial imagery, specifically for distinguishing between drones and helicopters, is diverse, yet it is relatively sparse when it comes to applying Naïve Bayes classifiers with specific feature extraction methods such as RGB averages and order-1 statistics. Below, we highlight key works that have directly or indirectly contributed to the development of methodologies related to this research.

One important study explored the role of Unmanned Aerial Vehicles (UAVs) and helicopters in security and surveillance applications. The research emphasized the importance of efficient classification systems for UAVs, which are increasingly used in applications ranging from border security to wildlife monitoring. It specifically discussed challenges in differentiating between various aerial platforms, making it clear that there is a need for robust classification methods that can handle the visual similarities between UAVs and other flying objects, including helicopters. This study provides foundational insights into the necessity of accurate and reliable classification systems for UAVs, a core issue that this research aims to address by applying Naïve Bayes and feature extraction techniques [9].

A method for pattern recognition in aerial imagery using advanced image processing techniques was also introduced. This study focused on leveraging machine learning models, including Naïve Bayes, for distinguishing between various objects captured by aerial platforms, such as drones and helicopters. The research demonstrated that despite the similarities in appearance, particularly when viewed from certain angles, machine learning algorithms could achieve significant classification accuracy. This paper is closely related to our work because it highlights the critical importance of model selection and feature extraction in aerial image classification, serving as a strong basis for the current research's use of Naïve Bayes and RGB-based features [10].

Another key paper presented a comprehensive evaluation of Naïve Bayes as a classifier for image datasets, with a particular focus on drone and helicopter images. It discussed the effectiveness of Naïve Bayes in terms of computational efficiency and simplicity, making it an attractive choice for real-time systems, even when the assumption of feature independence is not strictly met. The authors emphasized that Naïve Bayes could outperform more complex models when coupled with proper feature selection and pre-processing. This research serves as a justification for choosing Naïve Bayes as the classifier in our study, particularly for its efficiency in handling datasets with relatively small or medium sample sizes, typical of aerial imagery data [11].

Further, significant background on RGB feature extraction and its role in object classification is provided in a seminal text on digital image processing. The work discusses the fundamental concepts of image processing, including color models like RGB, and how these models can be used to extract meaningful features for image classification. This reference supports the use of RGB-based features in our classification pipeline, where the average RGB values serve as important inputs to the Naïve Bayes classifier [12]. Another relevant study presented a detailed comparison of various texture extraction methods for remote sensing images. It was valuable for understanding the role of texture features, such as those derived from order-1 statistics, in enhancing the performance of image classification tasks. By examining skewness, kurtosis, and variance in pixel intensity distributions, the research demonstrated how texture features could provide critical information about object boundaries and surface properties, which is particularly useful for distinguishing between objects like drones and helicopters in aerial imagery. This paper directly informs the texture feature extraction component of our research, as it provides a solid basis for utilizing order-1 statistics to complement color-based features [13]. Lastly, a study conducted on the fusion of color and texture features for image classification in UAV-based applications highlighted the improvements in classification accuracy when combining RGB features with texture statistics such as mean and variance. The results showed that this combined approach significantly outperformed methods relying solely on either color or texture features. This paper is directly aligned with our approach, which similarly aims to combine both RGB and order-1 statistical features to improve classification performance for drone and helicopter images [14].

These key studies provide valuable insights into the methodologies and techniques used in aerial image classification. They form the basis for our work, which builds upon these existing approaches by applying Naïve Bayes to a combined set of RGB and texture features to improve the accuracy of classifying drone and helicopter imagery.

3. Proposed Method

The Methods section of this research proposal outlines the study design, methodology, and work plan that will guide the investigation. It provides a detailed description of the processes and steps necessary to conduct the research, from data collection and preprocessing to model training and evaluation.

3.1. Study Design

This study adopts a quantitative experimental design aimed at comparing the classification performance of drone and helicopter images using the Naïve Bayes algorithm. The primary focus of this research is to evaluate classification accuracy using two feature sets: the mean values of the Red-Green-Blue (RGB) color channels and first-order statistical features derived from pixel intensity distributions [9], [11]. The study utilizes an aerial image dataset containing labeled images of drones and helicopters obtained from publicly available sources [15], [16], [17]. These images will be annotated according to the relevant object classes (drone or helicopter) to facilitate supervised machine learning tasks [13], [14]. Fig. 1 illustrates the overall study design employed in this research.

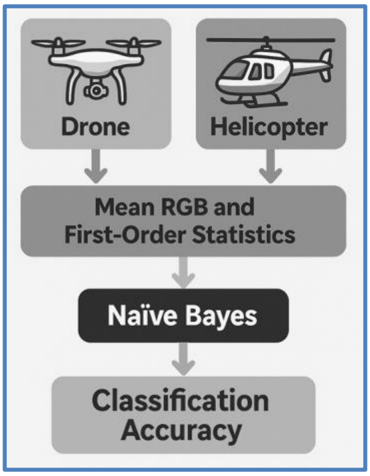

Fig. 1. Study Design Classification

3.2. Naïve Bayes

Naive Bayes has proven effective in many practical applications, including text classification, medical diagnosis, and systems performance management. In this paper, we utilize Naive Bayes to calculate the probability of data falling into a certain class based on the values of Drone and Helicopter image features. This study adopts the Naive Bayes algorithm as a probabilistic classification model built upon Bayes' Theorem, which calculates the probability of a class given a set of input features. The fundamental formula is:

$$P(C_k \mid \mathrm{x}) = \frac{P(C_k) \cdot P(\mathrm{x} \mid C_k)}{P(\mathrm{x})} \quad (1)$$

This expression calculates the **posterior probability** $P(C_k \mid \mathrm{x})$, or the probability that an input vector $x = (x_1, x_2, \dots, x_n)$ belongs to class C_k, using three components: the **prior probability** of the class $P(C_k)$, the **likelihood** of the features given the class $P(x \mid C_k)$, and the **marginal probability** of the features $P(x)$. The algorithm assumes that each feature x_i is conditionally independent of the others given the class, which simplifies the likelihood term into a product of individual feature probabilities:

$$P(\mathbf{x} \mid C_k) = \prod_{i=1}^{n} P(x_i \mid C_k) \quad (2)$$

This naive independence assumption makes computation tractable even with high-dimensional data. The classification is done by choosing the class with the highest posterior probability, resulting in the decision rule:

$$\hat{C} = \arg\max_{C_k} P(C_k) \prod_{i=1}^{n} P(x_i \mid C_k) \quad (3)$$

In practice, to prevent computational underflow from multiplying many small probabilities, the model uses the logarithmic form of the equation:

$$\hat{C} = \arg\max_{C_k} [\log P(C_k) + \sum_{i=1}^{n} \log P(x_i | C_k)] \quad (4)$$

This transformation retains the ranking of probabilities while where the likelihood $P(x_i \mid C_k)$ is modeled using a normal distribution parameterized by class-specific means and variances.

3.3. Methodology

a. Data Collection

The dataset for this study will be sourced from public aerial image repositories and specialized datasets containing drone images [13], [14], [15]. Previous studies have shown that the use of diverse datasets can enhance the quality and accuracy of image classification models [16], [17], [18], [19], [20], [21], particularly in remote sensing and aerial image analysis applications [22]. Moreover, ensuring variation in image capture conditions enables the model to be more robust against different environmental changes [22]. Fig. 2 and Fig. 3 present sample images from the drone and helicopter datasets used in this study.

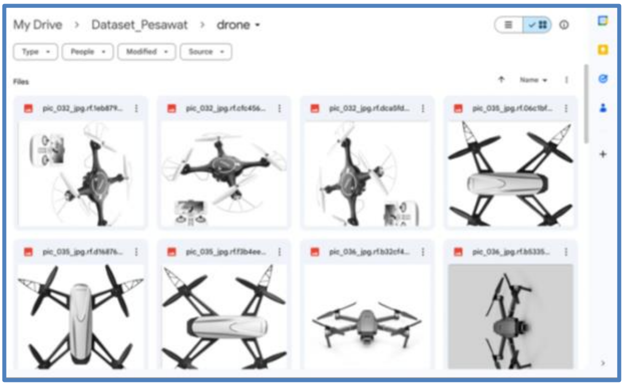

Fig. 2. Sample Drone Images from the Dataset

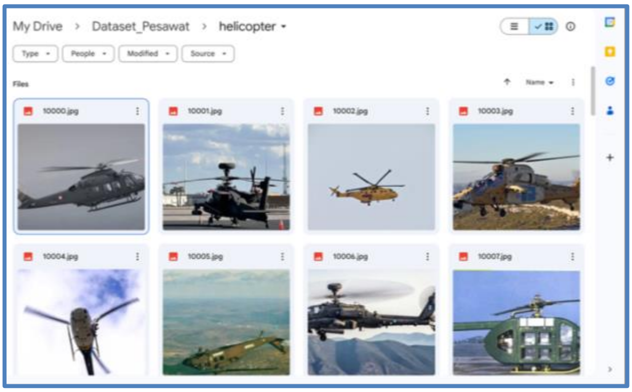

Fig. 3. Sample Helicopter Images from the Dataset

b. Feature Extraction

Feature extraction will be carried out in two main stages, as illustrated in Fig. 4:

1) RGB Features**:** The mean values for each of the Red, Green, and Blue (RGB) color channels will be calculated for each image. These features are expected to provide basic color information that can assist in distinguishing between drones and helicopters. The use of RGB-based features for image classification in aerial object recognition is effective in various prior studies [24].
2) **First-Order Statistical Features:** First-order statistical features, such as mean, variance, skewness, and kurtosis of pixel intensity distributions, will be computed for each image. These features are designed to capture texture and intensity patterns within the image, providing additional discriminatory power for distinguishing visually similar objects. Such statistical features are widely used in image-processing tasks to improve classification accuracy, particularly under varying lighting conditions [25].

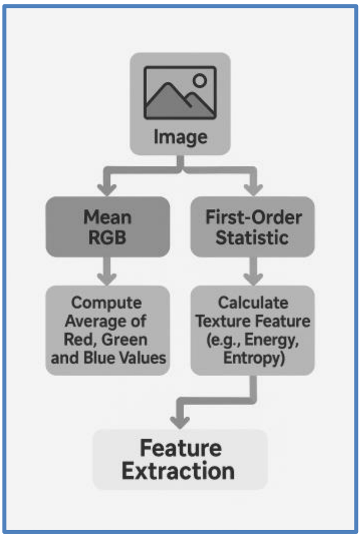

Fig. 3. Feature extraction image

Feature extraction was performed using Google Colab tools to compute color features based on the mean values of Red, Green, and Blue (RGB) channels, as well as texture features using first-order statistical methods, including mean, variance, skewness, and kurtosis derived from the pixel intensity distributions. The results of the feature extraction are presented in Fig. 4 and Fig.5.

Folder	Nama File	R (Red)	G (Green)	B (Blue)
drone	pic_036_jpg.rf.fab76c	23.155.635.986.328.100	23.155.635.986.328.100	23.155.635.986.328.100
drone	pic_048_jpg.rf.77817	240.149.091.796.875	240.149.091.796.875	240.149.091.796.875
drone	pic_036_jpg.rf.b32cf4	239.574.755.859.375	239.574.755.859.375	239.574.755.859.375
drone	pic_045_jpg.rf.b5b46	22.036.897.705.078.100	22.036.897.705.078.100	22.036.897.705.078.100
drone	pic_036_jpg.rf.b5335	1.933.525.146.484.370	1.933.525.146.484.370	1.933.525.146.484.370
drone	pic_045_jpg.rf.c818d	24.951.617.431.640.600	24.951.617.431.640.600	24.951.617.431.640.600
drone	pic_039_jpg.rf.2f9efb	20.469.947.265.625	20.469.947.265.625	20.469.947.265.625
drone	pic_048_jpg.rf.10a4d	235.237.216.796.875	235.237.216.796.875	235.237.216.796.875
drone	pic_044_jpg.rf.61b4b	22.022.484.375	22.022.484.375	22.022.484.375
drone	pic_042_jpg.rf.ba0da	173.374.306.640.625	173.374.306.640.625	173.374.306.640.625
drone	pic_035_jpg.rf.f3b4ee	2.203.199.072.265.620	2.203.199.072.265.620	2.203.199.072.265.620
drone	pic_042_jpg.rf.b4314	173.670.712.890.625	173.670.712.890.625	173.670.712.890.625
drone	pic_044_jpg.rf.a03e8	24.059.537.353.515.600	24.059.537.353.515.600	24.059.537.353.515.600
drone	pic_043_jpg.rf.b537b	244.946.982.421.875	244.946.982.421.875	244.946.982.421.875
drone	pic_039_jpg.rf.1979b	24.600.290.771.484.300	24.600.290.771.484.300	24.600.290.771.484.300
drone	pic_035_jpg.rf.d1687	21.734.117.431.640.600	21.734.117.431.640.600	21.734.117.431.640.600
drone	pic_048_jpg.rf.8f8a70	20.194.415.283.203.100	20.194.415.283.203.100	20.194.415.283.203.100
drone	pic_032_jpg.rf.1eb87	235.958.740.234.375	235.958.740.234.375	235.958.740.234.375
drone	pic_039_jpg.rf.94284	2.500.370.166.015.620	2.500.370.166.015.620	2.500.370.166.015.620
drone	pic_032_jpg.rf.cfc456	234.543.779.296.875	234.543.779.296.875	234.543.779.296.875
drone	pic_043_jpg.rf.7aedd	201.242.265.625	201.242.265.625	201.242.265.625
drone	pic_032_jpg.rf.dca5fc	23.605.061.767.578.100	23.605.061.767.578.100	23.605.061.767.578.100
drone	pic_044_jpg.rf.3e12f5	24.309.673.828.125	24.309.673.828.125	24.309.673.828.125
drone	pic_045_jpg.rf.a8422	24.339.335.205.078.100	24.339.335.205.078.100	24.339.335.205.078.100
drone	pic_035_jpg.rf.06c1b	216.922.548.828.125	216.922.548.828.125	216.922.548.828.125
drone	pic_042_jpg.rf.a8bb3	19.613.593.994.140.600	19.613.593.994.140.600	19.613.593.994.140.600
drone	pic_043_jpg.rf.4b2e0	242.287.119.140.625	242.287.119.140.625	242.287.119.140.625
drone	pic_038_jpg.rf.0b1b8	193.422.509.765.625	193.422.509.765.625	193.422.509.765.625
drone	pic_038_jpg.rf.aaa45	1.449.017.333.984.370	1.449.017.333.984.370	1.449.017.333.984.370
drone	pic_038_jpg.rf.f99818	6.022.253.662.109.370	6.022.253.662.109.370	6.022.253.662.109.370
helicopter	10115.jpg	18.297.600.108.337.500	19.779.608.399.033.500	22.171.207.839.449.500
helicopter	10040.jpg	10.624.892.577.620.800	10.437.623.492.797.000	8.450.659.476.079.500
helicopter	10038.jpg	15.471.310.329.861.100	15.394.298.177.083.300	14.663.450.810.185.100
helicopter	10032.jpg	12.161.526.296.505.800	13.382.199.355.454.500	155.534.673.602.301
helicopter	10041.jpg	13.025.325.191.336.900	1.280.702.263.475.000	12.322.893.014.167.000
helicopter	10097.jpg	16.341.608.561.197.900	17.887.507.120.768.200	19.102.613.321.940.100
helicopter	10110.jpg	11.244.397.045.252.700	10.649.321.433.296.600	9.730.587.966.326.080
helicopter	10117.jpg	8.716.535.185.272.840	11.680.619.499.199.100	15.526.205.394.790.100
helicopter	10068.jpg	1.585.529.893.338.010	16.180.337.166.396.500	16.078.544.607.355.000
helicopter	10063.jpg	11.058.017.306.857.600	15.002.417.115.490.800	18.590.258.049.242.400

Fig. 4. Feature Extraction Results Using RGB Mean Values

G_kurtosis	G_median	G_min	G_max	B_mean	B_std	B_skewness	B_kurtosis	B_median	B_min	B_max	Folder	Nama File
10.581.872.114.693.700	234.00.00	0	255	22.022.484.375	460.797.919.223.644	-34.504.662.554.372.600	10.581.872.114.693.700	234.00.00	0	255	drone	pic_044_jpg.r
23.639.052.876.339.300	255.00.00	0	255	24.600.290.771.484.300	24.947.965.258.695.900	-4.381.420.662.621.790	23.639.052.876.339.300	255.00.00	0	255	drone	pic_039_jpg.r
14.037.267.872.618.500	255.00.00	0	255	216.922.548.828.125	7.503.872.774.422.700	-17.613.121.150.526.500	14.037.267.872.618.500	255.00.00	0	255	drone	pic_035_jpg.r
4.224.148.544.564.210	255.00.00	0	255	24.951.617.431.640.600	20.758.092.880.419.200	-5.915.228.202.096.850	4.224.148.544.564.210	255.00.00	0	255	drone	pic_045_jpg.r
5.716.488.132.962.470	41.00.00	3	255	6.022.253.662.109.370	4.198.500.257.033.660	24.606.926.756.221.200	5.716.488.132.962.470	41.00.00	3	255	drone	pic_038_jpg.r
11.595.114.329.734.000	255.00.00	0	255	24.309.673.828.125	41.910.687.650.779.300	-35.845.358.095.624.100	11.595.114.329.734.000	255.00.00	0	255	drone	pic_044_jpg.r
13.604.565.986.715.300	186.00.00	0	255	173.374.306.640.625	5.075.768.551.342.160	-14.132.378.172.644.000	13.604.565.986.715.300	186.00.00	0	255	drone	pic_042_jpg.r
23.479.369.229.020.200	214.00.00	0	250	20.469.947.265.625	26.134.505.704.026.300	-4.414.943.777.148.070	23.479.369.229.020.200	214.00.00	0	250	drone	pic_039_jpg.r
17.529.650.805.754.400	232.00.00	0	255	22.036.897.705.078.100	29.370.963.834.721.600	-3.726.704.777.442.900	17.529.650.805.754.400	232.00.00	0	255	drone	pic_045_jpg.r
147.733.025.319.056	255.00.00	0	255	244.946.982.421.875	368.109.212.399.642	-39.072.943.110.014.400	147.733.025.319.056	255.00.00	0	255	drone	pic_043_jpg.r
14.438.716.072.439.700	255.00.00	0	255	21.734.117.431.640.600	7.456.052.274.324.510	-1.772.928.183.090.180	14.438.716.072.439.700	255.00.00	0	255	drone	pic_035_jpg.r
6.850.196.759.992.230	255.00.00	0	255	23.605.061.767.578.100	49.676.262.819.914.700	-28.132.730.697.202.600	6.850.196.759.992.230	255.00.00	0	255	drone	pic_032_jpg.r
75.513.441.971.852.100	209.00.00	0	255	1.933.525.146.484.370	44.768.041.339.942.700	-29.681.885.295.051.800	75.513.441.971.852.100	209.00.00	0	255	drone	pic_036_jpg.r
13.315.956.054.422.700	186.00.00	0	255	173.670.712.890.625	5.024.261.346.401.980	-14.055.827.438.908.800	13.315.956.054.422.700	186.00.00	0	255	drone	pic_042_jpg.r
8.724.428.861.759.470	00.00	0	255	1.449.017.333.984.370	35.735.412.590.413.200	291.822.344.151.231	8.724.428.861.759.470	00.00	0	255	drone	pic_038_jpg.r
4.706.739.085.756.880	255.00.00	0	255	235.237.216.796.875	53.960.476.327.910.800	-25.198.195.221.228.500	4.706.739.085.756.880	255.00.00	0	255	drone	pic_048_jpg.r
6.440.636.102.297.510	255.00.00	0	255	234.543.779.296.875	5.121.010.782.960.760	-27.398.019.571.246.000	6.440.636.102.297.510	255.00.00	0	255	drone	pic_032_jpg.r
12.499.944.768.731.500	255.00.00	0	255	242.287.119.140.625	4.443.198.941.858.030	-36.500.751.562.153.100	12.499.944.768.731.500	255.00.00	0	255	drone	pic_043_jpg.r
49.474.884.753.375.900	255.00.00	0	255	2.500.370.166.015.620	21.012.966.999.330.600	-6.450.951.169.632.210	49.474.884.753.375.900	255.00.00	0	255	drone	pic_039_jpg.r
10.922.812.265.162.800	214.00.00	0	255	201.242.265.625	4.381.582.641.330.640	-3.481.605.093.572.220	10.922.812.265.162.800	214.00.00	0	255	drone	pic_043_jpg.r
14.102.871.890.500.700	209.00.00	0	255	19.613.593.994.140.600	50.457.306.697.255.600	-1.447.214.856.775.110	14.102.871.890.500.700	209.00.00	0	255	drone	pic_042_jpg.r
608.796.107.058.132	00.00	0	255	193.422.509.765.625	4.219.078.711.744.250	2.504.437.826.664.490	608.796.107.058.132	00.00	0	255	drone	pic_038_jpg.r
68.634.834.590.310.300	255.00.00	0	255	235.958.740.234.375	4.978.900.463.156.550	-28.137.924.057.527.300	68.634.834.590.310.300	255.00.00	0	255	drone	pic_032_jpg.r
4.505.791.445.950.350	222.00.00	0	255	20.194.415.283.203.100	5.449.177.330.702.870	-24.842.995.520.159.000	4.505.791.445.950.350	222.00.00	0	255	drone	pic_048_jpg.r
10.948.762.088.147.500	254.00.00	0	255	24.059.537.353.515.600	45.230.275.349.434.500	-3.500.596.514.650.240	10.948.762.088.147.500	254.00.00	0	255	drone	pic_044_jpg.r
803.413.206.544.335	255.00.00	0	255	239.574.755.859.375	4.444.356.924.357.400	-30.292.424.537.684.700	803.413.206.544.335	255.00.00	0	255	drone	pic_036_jpg.r
8.038.197.883.272.710	247.00.00	0	255	23.155.635.986.328.100	4.455.120.887.515.490	-3.028.032.684.283.540	8.038.197.883.272.710	247.00.00	0	255	drone	pic_036_jpg.r
5.934.426.564.197.260	255.00.00	0	255	240.149.091.796.875	4.133.923.159.071.900	-26.876.663.457.667.300	5.934.426.564.197.260	255.00.00	0	255	drone	pic_048_jpg.r
15.723.280.753.152.800	255.00.00	0	255	2.203.199.072.265.620	7.035.354.307.797.300	-18.150.184.786.537.800	15.723.280.753.152.800	255.00.00	0	255	drone	pic_035_jpg.r
17.881.546.243.142.700	255.00.00	0	255	24.339.335.205.078.100	29.202.129.351.073.000	-37.501.129.510.223.000	17.881.546.243.142.700	255.00.00	0	255	drone	pic_045_jpg.r
-15.414.719.922.288.100	132.00.00	0	255	13.750.867.217.459.900	8.296.015.928.276.780	0.12159873990375646	-1.538.397.516.111.930	122.00.00	0	255	helicopter	10020.jpg
17.483.233.464.175.400	145.00.00	17	255	1.434.853.977.230.990	2.972.831.664.048.600	-15.297.887.002.855.300	2.184.925.482.705.270	154.00.00	11	255	helicopter	10000.jpg
-15.043.336.377.392.400	137.00.00	0	255	12.584.674.213.353.700	8.351.394.216.427.350	0.07532630597685054	-16.072.319.157.387.400	124.00.00	0	255	helicopter	10019.jpg
0.9118234833271552	41.00.00	0	255	5.331.703.974.027.880	5.148.246.240.166.480	0.8262873419050732	-0.3826721470186767	46.00.00	0	255	helicopter	10017.jpg
-15.841.031.856.771.800	91.00.00	0	255	11.297.930.633.670.700	6.495.854.609.264.950	0.002534765547811099	-1.591.004.561.893.890	99.00.00	0	255	helicopter	10009.jpg
41.013.468.455.089	107.00.00	10	255	177.442.969.064.349	2.585.588.338.011.030	-23.825.297.220.300.500	8.358.011.446.776.330	178.00.00	31	255	helicopter	10018.jpg
2.527.708.985.646.500	206.00.00	0	254	21.142.473.527.645.000	31.486.322.497.069.300	-4.671.901.468.833.820	2.105.106.342.922.880	219.00.00	0	255	helicopter	10002.jpg
-15.092.046.588.190.000	99.00.00	17	255	15.570.089.066.326.800	7.806.724.849.299.590	0.2031634324729369	-15.928.100.697.054.500	130.00.00	21	255	helicopter	10011.jpg
-1.194.713.609.090.530	193.00.00	9	255	1.575.911.325.301.200	7.069.607.073.772.570	-0.51877528591963	-14.989.653.389.341.400	207.00.00	6	255	helicopter	10016.jpg
7.643.093.275.443.690	144.00.00	0	255	18.799.466.885.887.900	4.146.691.575.780.760	-2.954.501.267.621.310	8.582.651.633.435.350	197.00.00	0	255	helicopter	10014.jpg
-10.014.366.029.443.500	164.00.00	0	255	12.145.710.986.730.000	7.338.874.722.141.570	0.5273137038890072	-10.870.861.456.393.300	98.00.00	0	255	helicopter	10013.jpg

Fig. 5. Feature Extraction Results Using First-Order Statistical Features Values

c. Data Preprocessing

Before modelling, the dataset will undergo a series of preprocessing steps to ensure optimal data quality. First, image scaling will be performed by resizing all images to a uniform resolution, ensuring consistency across the dataset. This step is crucial for reducing noise that could impact model performance, thereby enabling more stable and reliable results [26]. Second, pixel intensity values will be normalized to a range between 0 and 1 to enhance model stability and accelerate convergence during training.

This normalization process has been proven effective in improving the performance of image-based models, particularly in speeding up convergence on large datasets [27]. Lastly, data augmentation will be applied using techniques such as rotation, flipping, and scaling to increase dataset diversity and reduce the likelihood of model overfitting. These augmentation techniques are highly beneficial for improving model generalization, especially when working with limited datasets, by introducing greater variation in the training data [28], [29]. Fig. 5 shows the interface when setting the attribute index parameters for feature selection.

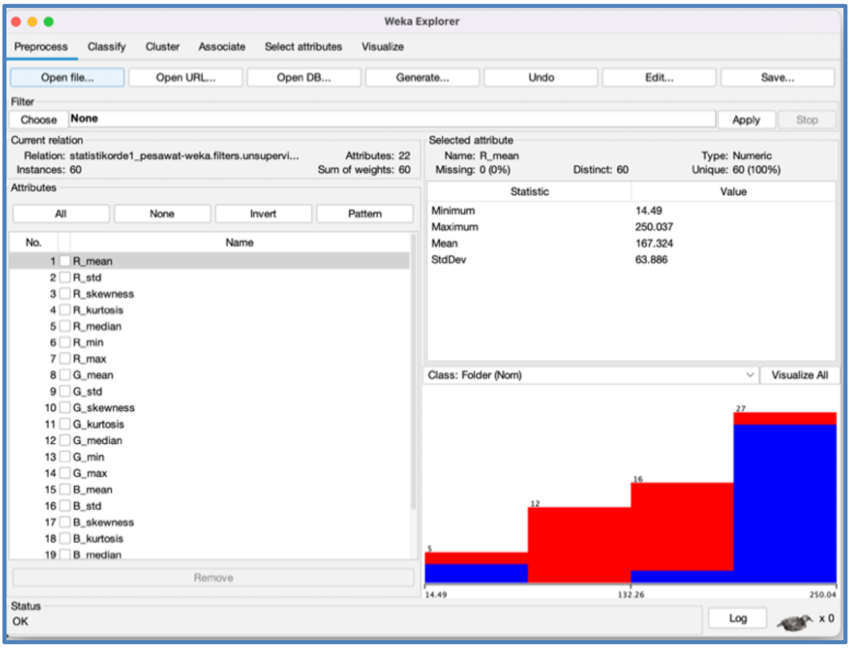

Fig. 5. The interface when setting the attribute index parameters for feature selection

d. Model Training

Image classification will be performed using the Naïve Bayes algorithm, as illustrated in Fig. 6. The model will be trained using two separate feature sets—RGB mean values and first-order statistical features—as well as their combination. The dataset will be split with 80% allocated for the training set and 20% for the testing set, ensuring a balanced representation of drone and helicopter images in both subsets. Naïve Bayes has proven to be an effective algorithm for image classification, particularly with smaller and simpler datasets, despite its assumption of feature independence, which is often not fully satisfied in practice [30].

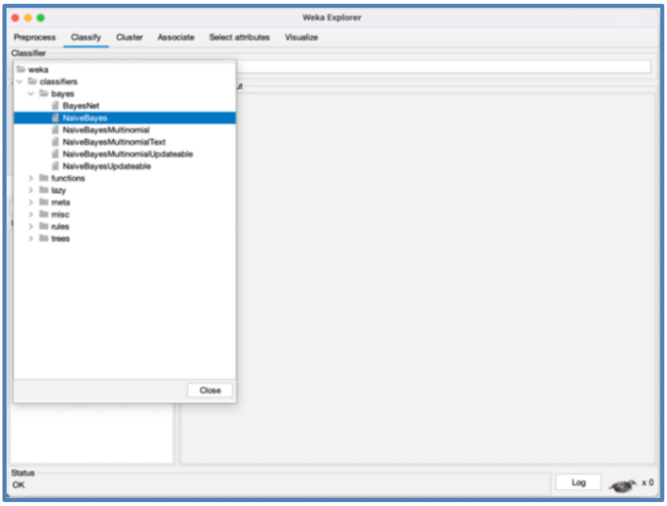

Fig. 6. Naïve Bayes Classification Process

e. Model Evaluation

The performance of the Naïve Bayes classifier will be evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. Accuracy measures the proportion of correct predictions out of all predictions made, providing an overall assessment of how well the model classifies the data. Precision evaluates the proportion of true positive predictions among all positive predictions, which is important for assessing the correctness of positive class predictions. Recall, on the other hand, measures the proportion of true positive predictions among all actual positive instances, reflecting the model's ability to detect all relevant positive cases. The F1-score, which is the harmonic mean of precision and recall, offers a balanced view of model performance, particularly useful in cases of class imbalance between positive and negative categories. In addition, cross-validation will be applied to assess the model's stability and robustness against different data samples and to reduce the risk of overfitting. Cross-validation is a widely used technique in machine learning to ensure that a model not only performs well on training data but also generalizes reliably to unseen data [27], [30], [31], [32], [33].

4. Results and Analysis

The classification results using the Naïve Bayes method with two different feature extraction approaches which RGB features and first-order statistical features—are summarized in Table 1. These results show a significant difference in terms of model accuracy and overall performance. For the model using RGB features, extracted from the mean values of the red, green, and blue color channels, the achieved accuracy is 91.67%, indicating that RGB features are highly effective in distinguishing between drone and helicopter images. The precision for the drone class is 88.9%, while for the helicopter class it is 100%, meaning that all helicopter predictions were correct with no false positives. Furthermore, the model achieved 100% recall for drones, although only 75% of helicopters were correctly identified, suggesting that while the model is very effective at detecting drones, it has slight limitations in identifying helicopters. The ROC Area value of 1.0 further demonstrates the model's perfect ability to distinguish between the two classes with no overlap or confusion.

In contrast, the model using first-order statistical features, which include mean, standard deviation, skewness, and kurtosis of pixel intensity distributions, achieved a lower accuracy of 75%. While this is still reasonably good, it is not as strong as the RGB-based model in differentiating between drones and helicopters. The precision for the drone class is 85.7%, but only 60% for helicopters, indicating more misclassifications for helicopters compared to drones. Both classes recorded a recall of 75%, meaning the model was able to detect most of the images in each class, though this is lower than the 100% recall achieved by the RGB model for drones. The ROC Area value of 0.938 suggests that the model still performs well in distinguishing between the classes, although its discriminative ability is slightly inferior to the RGB feature model.

Table 1. Model Testing and Evaluation Results

Feature Type	Accuracy	Precision (Drone)	Precision (Helicopter)	Recall (Drone)	Recall (Helicopter)	ROC Area
Mean RGB	91.67%	88.9%	100%	100%	75%	1.000
First-Order Statistics	75.00%	85.7%	60%	75%	75%	0.938

In this study, a comparison was made between RGB feature extraction and first-order statistics in classifying drone and helicopter images, revealing significant differences in model performance. The RGB feature-based model achieved a high accuracy of 91.67%, with precision values of 88.9% for drones and 100% for helicopters, and recall values of 100% for drones and 75% for helicopters. In contrast, the first-order statistics model had an accuracy of 75%, precision values of 85.7% for drones and 60% for helicopters, and recall values of 75% for both classes. The Area Under the Curve (AUC) ROC for the RGB model was 1.0, indicating perfect class separation, while the first-order statistics model showed an AUC ROC of 0.938, indicating excellent but not perfect class separation.

Previous research supports these findings. A study [34] reported that the use of RGB images from UAVs for classifying roof materials achieved over 95% accuracy, demonstrating the effectiveness of RGB features in UAV-based image classification. Furthermore, another research [35] found that although first-order statistics such as skewness and kurtosis are effective in medical image analysis, their performance is not as high as texture-based methods in general image classification tasks.

In this study, the proposed method using RGB mean features achieved a classification accuracy of 91.67% with an AUC of 1.0, while the method using first-order statistical features only reached 75% accuracy with an AUC of 0.938. This significant gap of over 16 percentage points clearly shows that RGB-based features are more discriminative in distinguishing visual patterns between drones and helicopters. The high AUC value also indicates that the RGB feature-based model can reliably differentiate between the two classes across different threshold values. These findings reaffirm that RGB features offer a stronger basis for classification in aerial imagery due to their ability to capture dominant colour characteristics that vary between drones and helicopters. In contrast, first-order statistical features, while informative about the distribution and texture of pixel intensities lack the spatial and chromatic sensitivity required for optimal classification in this context. However, first-order statistics should not be disregarded entirely. They provide complementary insights into pixel intensity variation, which can be valuable in edge cases or low-light conditions where colour cues may be diminished. Therefore, a combination of RGB features and first-order statistics could serve as an enhanced feature set, potentially improving classification robustness in varied real-world scenarios. This comparative analysis demonstrates the effectiveness of the proposed method and supports the use of simple, interpretable features in image classification, especially when computational efficiency and real-time performance are prioritized.

6. Conclusion

This study investigated the effectiveness of the Naïve Bayes classification algorithm for distinguishing between drone and helicopter images by comparing two types of features: RGB mean values and first-order statistical features (mean, standard deviation, skewness, kurtosis). Using a dataset of 60 aerial images, the RGB-based feature model achieved the highest performance, with an accuracy of 91.67%, precision scores of 88.9% for drones and 100% for helicopters, and an AUC (Area Under Curve) of 1.0. In contrast, the model based on first-order statistics reached only 75% accuracy, with lower precision, recall, and an AUC of 0.938. These results highlight that RGB colour information provides stronger discriminative power in identifying visual differences between drones and helicopters, making it more effective for UAV-based image classification tasks. Although first-order statistical features offered useful insights into pixel intensity distributions, their sensitivity to shape and colour variations was limited. Nevertheless, these features still hold potential as complementary inputs in more advanced classification systems. The main contribution of this research lies in demonstrating that a lightweight, interpretable algorithm like Naïve Bayes, when paired with appropriate low-level features, can produce competitive results in image classification without the need for complex deep learning models. This approach is particularly valuable in scenarios with limited computational resources or in real-time UAV applications. Future improvements could involve combining RGB features with more complex statistical or texture-based descriptors to enhance accuracy and robustness. Expanding the dataset to include a wider range of images under diverse lighting, angles, and environmental conditions would also improve generalizability. Furthermore, optimizing the classification pipeline for real-time integration into UAV systems can support practical use in surveillance and monitoring. Extending the model to handle multi-class aerial object classification and incorporating additional sensor data, such as thermal or LiDAR imagery, could further improve performance, especially in visually challenging environments. Through these developments, the study contributes to the advancement of efficient and reliable aerial object recognition systems.

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