Smart Agricultural Sprayer System using Weighted KNN on Autonomous Farming Drones

Arjon Turnip, Mohammad Taufik, Poltak Sihombing, Endra Joelianto, and Noman Naseer

***Abstract*— Precision agriculture has gained significant attention for its potential to optimize resource use and enhance crop productivity. Autonomous drones equipped with smart systems are increasingly being used for tasks such as watering, fertilization, and monitoring. This paper presents the development and evaluation of a Smart Sprayer system that utilizes an autonomous drone for precise water discharge control. The system employs a weighted K-Nearest Neighbors (KNN) algorithm to classify watering intensity, achieving an accuracy of 90.7%. A dataset of 3,750 samples was used, evenly distributed across six classes (Stop, Very Low, Low, Medium, High, and Very High) and split 80:20 for training and testing. The model demonstrated strong performance in key metrics such as Precision and Recall, excelling particularly in predicting features like Altitude and Sprayer Valve, as reflected in high Positive Predictive Values and low False Discovery Rates. However, challenges remain in accurately classifying certain features, including Drone Velocity and GPS Error, where lower Precision and higher False Discovery Rates were observed. These limitations highlight the need for further model refinement and tuning. Future work will focus on real-world deployment and hardware optimizations to enhance system performance in autonomous agricultural operations.**

***Index Terms*— Smart agriculture, Autonomous farming drones, K-Nearest Neighbors, Sprayer system, Wireless.**

I. Introduction

AS an agricultural country, Indonesia's agricultural sector not only fulfills the food needs of its population but also plays a significant role in the national economy [1][2]. Agriculture serves as the backbone of Indonesia's economy, contributing 14% to the national GDP. Additionally, 33% of the workforce is employed in the agricultural sector, making it the second-largest sector in terms of labor absorption, particularly in livestock farming. However, the contribution of agriculture to Indonesia's GDP has begun to decline [3].

Productivity in the agricultural and food sectors has faced numerous challenges in recent years. These challenges stem from several factors, including the shrinking availability of agricultural land, the depletion of natural resources, and the slow advancement of agricultural technology due to the continued reliance on traditional methods [4]. One potential solution is the integration of modern technology into agriculture. This can be achieved through the implementation of smart agriculture using unmanned aerial vehicles (UAVs), enabling autonomous agricultural operations and reducing human labor dependency [5-7].

UAVs offer relatively low operating costs and are designed for high maneuverability, allowing them to access hard-to-reach areas with ease. Their compact size enables them to fly at low altitudes over crops, ensuring high precision in various tasks such as real-time crop monitoring, pesticide spraying, and irrigation. By automating tasks that traditionally required substantial human labor, UAV technology enhances both operational efficiency and effectiveness. Moreover, UAVs can be equipped with advanced sensors, including multispectral and thermal cameras, to provide detailed, real-time data on crop and soil conditions. This data empowers farmers to make informed and timely decisions, ultimately improving agricultural productivity and reducing costs. The adoption of UAV technology not only yields significant economic benefits but also supports more sustainable agricultural practices [7-9].

The potential of agricultural productivity has yet to be fully realized, primarily due to inefficiencies in crop monitoring, irrigation patterns, and pesticide application over large areas of farmland [10][11]. To address these challenges, the use of drones has become essential. By integrating flight controllers, drones can autonomously perform spraying over extensive fields while accounting for various factors to enhance irrigation efficiency [12][13]. Therefore, developing an autonomous drone-based irrigation system that considers variables such as speed, spraying power, and soil coverage is necessary to maximize the effectiveness of drone utilization.

Several studies have been conducted on the use of autonomous drones for pesticide spraying. In this context, analyzing droplet deposition characteristics has been a key focus in pesticide application research. The study conducted in [14] identified several independent factors that influence the deposition characteristics of droplets sprayed by UAVs. Additionally, in UAV-based spraying, optimizing influencing parameters can enhance precision in plant irrigation. In [15], an experiment was conducted to assess the effectiveness of canopy

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structures using four factors: Spray Application Volume Rate (SV), Flight Speed (FS), Flight Height (FH), and Flight Direction (FD). Similarly, [16] examined air spraying and droplet distribution using the Box-Behnken method.

The development of UAV spraying systems extends beyond hardware improvements. To enhance accuracy and efficiency, researchers have also explored machine learning integration. Recent advancements in computing and data availability have driven progress in machine learning, particularly deep learning [17]. Numerous studies have examined machine learning applications in UAVs. In [18], an analysis of the latest advancements and trends in reinforcement learning (RL)-based UAV applications was conducted, identifying potential future research directions. The application of machine learning in drone design and development can significantly enhance operational efficiency and effectiveness.

Machine learning encompasses various models for analyzing and classifying data, one of which is K-Nearest Neighbors (KNN) [19–21]. Given a dataset, the algorithm predicts relationships between new and existing data, classifying new inputs into the most suitable categories based on learned patterns [22–26]. This algorithm can be applied to improve the accuracy and efficiency of drone spraying by optimizing input parameters. In this study, KNN is proposed for classifying watering force using sensor data such as altitude, wind speed, and drone velocity.

This research focuses on developing an optimal irrigation method for agricultural drones using KNN. The objective is to establish an effective and efficient drone-based watering system that can be successfully implemented in the agricultural industry.

II. Method

A. Data Collection

This research was conducted at the Basic Science Service Center, Padjadjaran University, Indonesia, in an area designed to resemble agricultural land. The field test involved 12 drone flights, using four different trajectory types and three different altitudes. During the flights, data was collected on altitude, wind speed, drone speed, and latitude and longitude coordinates.

The drone used in this test had an F450 frame, and the flight controller was a Pixhawk 2.4.6, which managed flight and landing operations. The drone was equipped with an M8N SE100 Radiolink GPS module for location tracking during flight. A Raspberry Pi 4 was used as the microcontroller to run the Python program in this study, enabling wireless communication. For watering purposes, DC motors were used. The Pixhawk serves as the drone's primary controller, managing all aspects of flight, including flight commands, forward movement, and landing. Additionally, Pixhawk has the capability to store data such as altitude, drone location, and waypoints for flight missions.

In this study, the Mission Planner application was used for drone calibration and configuration. Mission Planner also enables the creation of flight missions by defining waypoints, which serve as the designated flight path for the drone to follow. The Micro Air Vehicle Link (MAVLink) protocol is used for telemetry and communication, facilitating the connection between Pixhawk, acting as the flight controller, and the Raspberry Pi 4, functioning as the microcontroller. By utilizing MAVLink, the Raspberry Pi can receive various types of drone data stored on Pixhawk.

The Raspberry Pi is responsible for controlling the watering force of the DC motor through a motor driver. It communicates with the motor using the Raspberry Pi's GPIO (General Purpose Input/Output) pins, which are configured via the Python library. The DC motor is connected to a water source through a small hose equipped with a watering nozzle. When the motor is activated, water is drawn and flows through the nozzle. The Raspberry Pi regulates the watering force by adjusting the voltage supplied to the motor driver. In the watering system, the data used to regulate watering force includes altitude, wind speed, and drone speed. Meanwhile, the decision to activate watering is based on predefined waypoint data assigned to the drone.

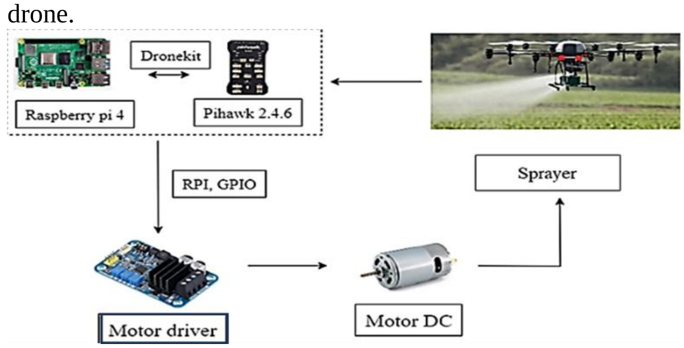

Fig. 1. Block Diagram of the Smart Sprayer System on a Sprayer Drone.

A. K-Nearest Neighbors (KNN) method

The data obtained from the variables is processed using the K-Nearest Neighbors (KNN) method. KNN is considered one of the simplest algorithms in machine learning. While it can be used for both classification and regression, it is more commonly applied to classification tasks. Given a dataset, the algorithm predicts the relationship between unseen data and existing data. Based on these predictions, it classifies new data into the most suitable categories. As a result, the KNN algorithm enables reliable classification of new data.

In this study, weighted KNN (wKNN) was used with the goal of developing a technique that does not rely on an arbitrary choice of k, which could lead to a high classification error. In this approach, the number of nearest neighbors is implicitly determined by the weight: if k is too large, it is automatically adjusted to a lower value.

For data calculation using the KNN method, the algorithm structure is described as follows. Suppose $L=\{(y_i, x_i), i = 1,\ldots,nL\}$ is a set of learnings from observations x_i with class membership given y_i, and suppose x is a new observation whose class y must be predicted. Then find k+1 nearest neighbors of x based on the distance function $d(x, x_{(i)})$. The neighbors to (k+1) are used for the normalization of k least distance via the formula:

$$D_{(i)} = Dx, \left(x_{(i)}\right) = \frac{d(x, x_{(i)})}{d(x, x_{(k+1)})} \tag{1}$$

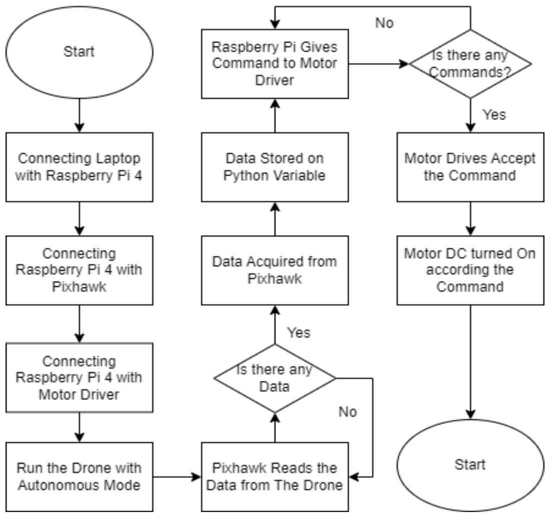

Fig. 2. Smart Sprayer System on Autonomous Drone Flowchart.

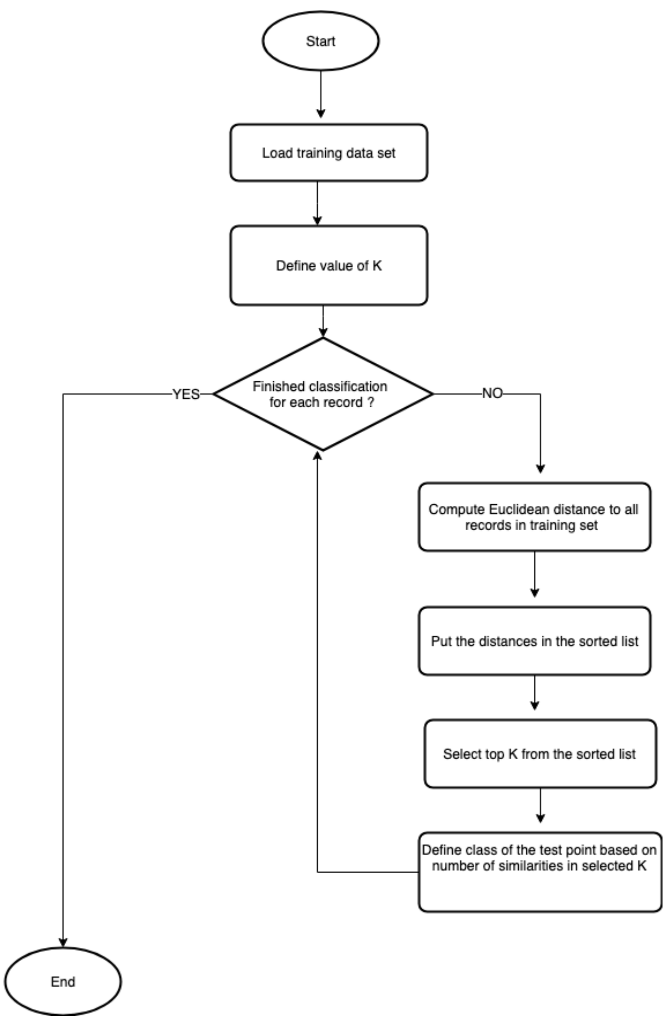

Fig. 3. K-Nearest Neighbors Flowchart.

which is a distance function for k+1 data. Next, transform the normalized distance $D_{(i)}$ using the kernel function K to the weight $w_{(i)} = K(D_{(i)})$. As a prediction for class y membership from observations x, select the class that shows the weighted majority of the nearest neighbors k. So that the following formula is obtained:

$$\hat{y} = max_r(\sum_{i=1}^{k} w_{(i)} I(y_{(i)} = r)) \tag{2}$$

where after the determination of the similarity size for the observations in the learning set, each new case (y,x) is classified into the class with the greatest weight added.

III. Results and Discussion

The data collection process involves gathering sensor measurements from the drone's smart sprayer. The collected data includes altitude, wind speed, drone speed, and GPS errors. The dataset comprises 3,750 samples, categorized into six distinct classes: Off, Very Low, Low, Medium, High, and Very High. Each class contains an equal number of 625 samples to ensure a balanced data distribution. Maintaining this balance is essential to prevent model bias toward classes with more data, which could lead to inaccurate predictions and degrade overall model performance. Fig. 4 presents the sensor measurement results from the drone's smart sprayer, while Table 1 provides a detailed description of the dataset.

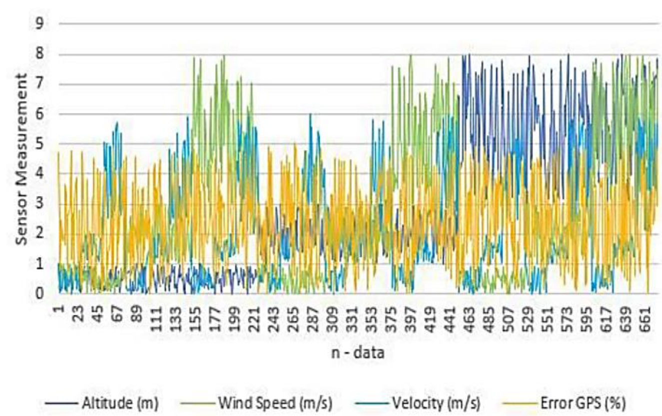

Fig. 4. Raw data from the drone's smart sprayer: Altitude (blue), wind speed (green), drone speed (sky blue), Error GPS (yellow).

When determining the classification range of data in a dataset, several methods can be employed, each offering distinct advantages. In this experiment, however, the Box Plot method was chosen for its ability to provide a clear and concise summary of data distribution. This method relies on five key statistical measures: the minimum, first quartile (Q1), median, third quartile (Q3), and maximum. These metrics not only offer insights into the central tendency and spread of the data but also help identify outliers and overall variability within the dataset. By leveraging the Box Plot method, we can visually and numerically refine classification ranges, enabling more precise categorizations. Its robustness lies in its ability to divide data into quartiles, making it particularly useful for datasets with

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skewed distributions or the presence of outliers. This enhances classification accuracy by ensuring that data is categorized based on meaningful thresholds rather than arbitrary divisions. The results of applying the Box Plot method to this dataset are illustrated in Fig. 5, where the transformation of data into quartiles can be observed.

TABLE I
SMART SPRAYING DRONE DATASET DESCRIPTION

	Altitude (m)	Wind Speed (m/s)	Velocity (m/s)	Error GPS (%)	Output
Count	3750	3750	3750	3750	3750
mean	3.8	3.73	3.01	3.74	2.5
Std	2.24	2.21	1.74	3.3	1.7
min	0.004	0.002	0.003	0.002	0
25%	1.87	1.88	1.5	1.5	1
50%	3.75	3.64	3.02	2.97	2.5
75%	5.6	5.5	4.54	4.45	4
Max	8	8	6	15	15

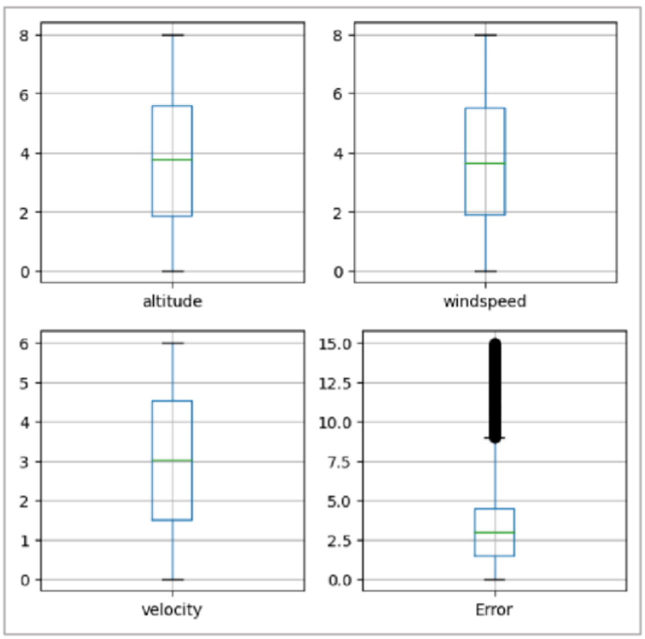

Fig. 5. Data Plot Results into Box Chart.

Each variable in a dataset exhibits some level of correlation with other variables, representing the strength and direction of their relationship. Correlations can be classified into two types: negative correlation, where the correlation coefficient is less than 0, indicating that as one variable increases, the other decreases, and positive correlation, where the coefficient is greater than 0, meaning both variables tend to increase or decrease together. When the correlation coefficient between two variables is exactly 0, it signifies the absence of any linear relationship between them (no correlation). In Fig. 6, the heatmap illustrates the relationships between variables in the dataset, helping to quickly assess which variables are strongly interconnected and which are independent. This visualization is particularly useful for identifying multicollinearity, where multiple variables are highly correlated, potentially affecting the performance of certain models like regression analysis.

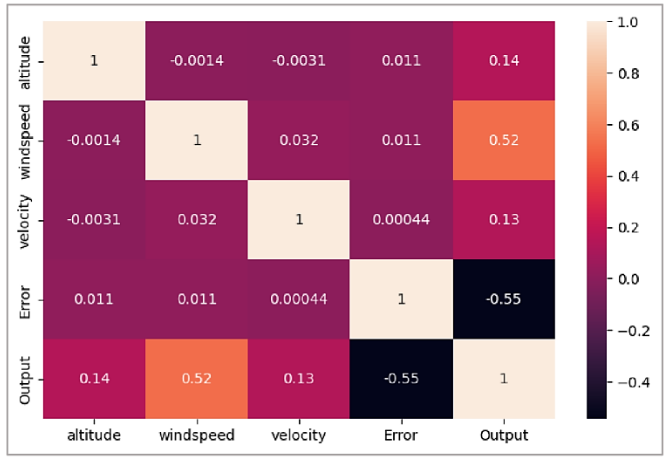

Fig. 6. Correlation Between Variables using Heatmaps

The heatmap table in Fig. 6 gives a correlation matrix of five variables: altitude, windspeed, drone velocity, GPS error, and output (sprayer valve). Each value in the matrix represents the correlation coefficient between two variables, which ranges from -1 to 1. Its correlation with windspeed (-0.0014) and velocity (-0.0031) is very close to zero, indicating no linear relationship between altitude and these variables. Altitude shows a weak positive correlation with error (0.011), but this is still quite minimal, suggesting almost no connection. The correlation with output (0.14) is stronger compared to the other variables but still weak. This implies a mild positive relationship between altitude and output, meaning as altitude increases, output slightly tends to increase. Windspeed and drone velocity have a weak negative correlation with altitude (-0.0014), and a very weak positive correlation with velocity (0.0032), respectively, again suggesting almost no connection. The correlation with error (0.011) is slightly positive but still insignificant. Interestingly, the correlation between windspeed and output (0.52) is moderate, indicating that higher windspeed might positively impact the output. This is a notable relationship worth further exploration.

Drone velocity shows weak negative correlations with altitude (-0.0031) and windspeed (0.0032), indicating no linear relationship. Its correlation with GPS error (0.000044) is extremely close to zero, meaning velocity and GPS error are almost completely uncorrelated. The correlation with output (0.13) is weak, showing only a slight positive relationship between velocity and output. GPS error has no strong relationships with altitude (0.011), windspeed (0.011), or velocity (0.000444), indicating almost no linear dependencies. However, the correlation between error and output (-0.55) is moderately negative, suggesting that as error increases, output decreases. This makes sense intuitively, as more errors could lead to reduced output performance. Output is positively correlated with altitude (0.14), windspeed (0.52), and velocity (0.13), suggesting that these factors might contribute to increased output, though the relationships are weak to moderate. Output has a negative correlation with error (-0.55), showing that higher error values result in lower output, which is a critical insight for optimization efforts. Altitude, windspeed, and velocity have mostly weak or negligible correlations with each other. Most of the variables have very weak correlations with each other, indicating limited interdependency, except for the relationships involving output.

Once the dataset is established, the next crucial step is developing the algorithm for the smart sprayer. This algorithm must include rules to determine the appropriate watering power based on various environmental variables. With the prepared dataset, which consists of 250 different conditions, the algorithm is designed to produce outputs that categorize watering power into six levels: Off, Very Low, Low, Medium, High, and Very High. In this study, K-Nearest Neighbors (KNN) algorithm was implemented to process the dataset. The features of the dataset, along with the prediction target, were carefully extracted and stored in separate variables for clarity and efficiency. The dataset was then split into a training set and a testing set in an 80:20 ratio, where 80% of the data was used to train the model, and 20% was reserved for testing its performance. This approach ensures that the model is exposed to a large portion of the data for learning while still being validated on unseen data to gauge its predictive accuracy.

A weighted KNN variant was employed in this case, representing an extension of the basic KNN algorithm. In weighted KNN, each neighbor contributes differently to the final classification, with weights assigned based on the distance from the query point. This method helps the algorithm give more influence to closer neighbors, typically using distance-inverse weights or kernel density estimates. By doing so, it improves the algorithm’s ability to make nuanced predictions, especially in cases where nearer points are more representative of the true condition. The use of weighted KNN is particularly relevant for a smart sprayer, as it allows the system to make more accurate and context-sensitive adjustments to the watering power based on sensor data. This is especially important when operating in diverse and unpredictable field conditions, where small changes in sensor readings can have significant impacts on the required water output. The results from the drone's sensor measurements, which reflect the algorithm's effectiveness, are illustrated in Fig. 7.

To evaluate the performance of the model, a Confusion Matrix is employed. The Confusion Matrix provides several important metrics that help assess how well the model performs. These metrics include Precision (also known as Positive Predictive Value, or PPV), Recall (or True Positive Rate, TPR), Support, False Positive Rate (FPR), and False Discovery Rate (FDR). These metrics are crucial in providing a nuanced understanding of the model's strengths and weaknesses. For example, while a high Precision suggests that the model makes few incorrect positive predictions, a lower FDR highlights that false positives are minimal compared to overall positive predictions. Additionally, the Recall metric provides insights into how many of the actual positive instances are detected by the model, which is vital for applications where missing positive cases could have significant consequences. In this particular case, the K-Nearest Neighbors (KNN) model achieved an overall accuracy of 90.7%, demonstrating strong performance in correctly classifying data points. The detailed performance results can be further examined in terms of specific metrics: the True Positive Rate (TPR) and False Negative Rate (FNR) are illustrated in Fig. 8, while the Precision (PPV) and False Discovery Rate (FDR) are shown in Fig. 9. These visualizations provide a clearer view of the model's performance across different categories and enable a more granular analysis of its predictive capabilities.

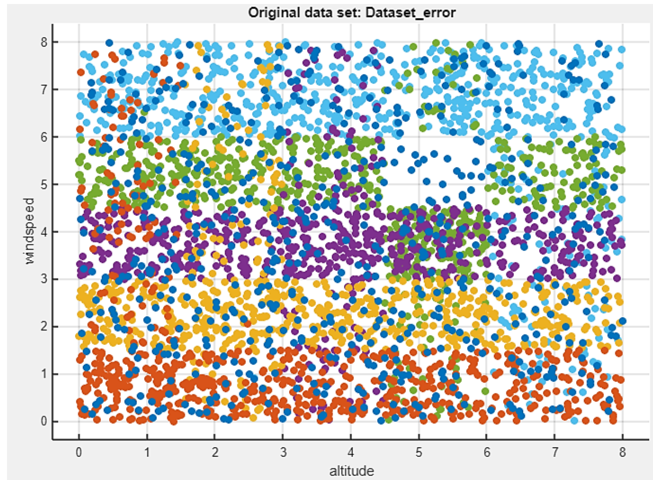

Fig. 7. Scatter Plot Data from Sensors.

Fig. 8 presents the True Positive Rate (TPR) and False Negative Rate (FNR) for six classes (Altitude, Wind Speed, Drone Velocity, GPS Error, and Sprayer Valve). These metrics are crucial in evaluating the performance of a classification model, particularly in determining its ability to correctly identify instances of each class. Altitude has the highest TPR (92%) and the lowest FNR (8%), indicating that the model is highly reliable for this class. GPS Error exhibits the lowest TPR (76.8%) and the highest FNR (23.2%), pointing to substantial challenges in correctly identifying instances of this class. Classes altitude, wind speed, and drone velocity have moderate TPRs ranging from 82.4% to 88.8%, and FNRs between 11.2% and 17.6%. These classes could benefit from improvements in feature differentiation or model tuning. Sprayer valve, with a TPR of 91.2% and FNR of 8.8%, also shows strong model performance, second only to Altitude. While the model performs well overall, particularly for altitude 0 and Sprayer valve, it faces significant challenges in accurately classifying GPS Error, which requires focused attention for performance improvement. Fine-tuning the model’s parameters or incorporating additional features might help in boosting performance, especially for the weaker classes.

Fig. 9 shows the performance of a classification model in predicting different features related to a drone’s performance under two metrics: PPV (Positive Predictive Value) and FDR (False Discovery Rate). These metrics are used to evaluate the accuracy and error of the predictions for each feature. The PPV is 88.80%, indicating a high level of precision in predicting the correct altitude. This suggests the model is good at predicting the true positives for altitude. The FDR is 11.20%, which complements the PPV, representing a relatively low false discovery rate. This means there are only a small number of false positives in altitude predictions, reinforcing the model's accuracy. With a PPV of 84.40%, the model performs well in

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predicting wind speed. This reflects good precision, with a strong ability to correctly identify true positives for wind speed. The FDR of 15.60% shows a slightly higher rate of false positives compared to altitude but is still relatively low, demonstrating that the model is reliable in predicting wind speed. The PPV drops to 76.50%, meaning the model is less precise in predicting drone velocity compared to altitude and wind speed. While this is still a reasonable value, it suggests more misclassifications.

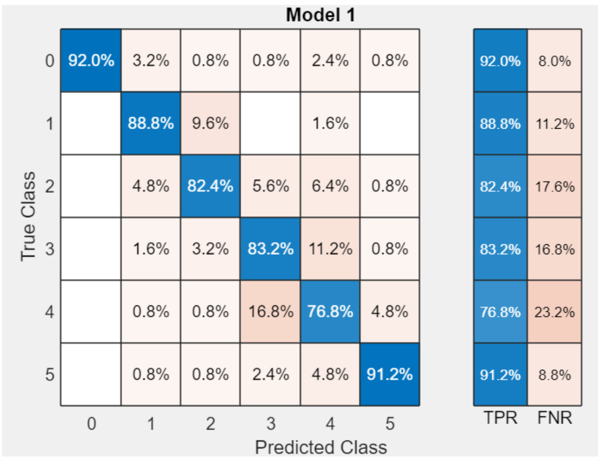

Fig. 8 Hasil TPR dan FNR Confusion Matrix.

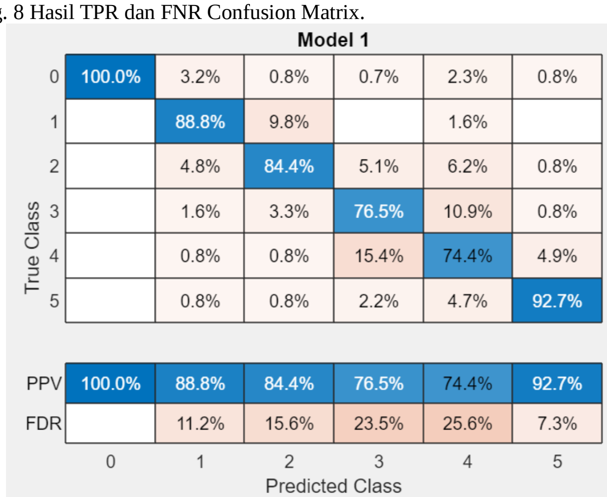

Fig. 9 PPV Results and FDR Confusion Matrix.

The FDR of 23.50% reflects a higher false discovery rate, indicating the model struggles more with correctly classifying drone velocity compared to other features. The PPV for GPS Error is 74.40%, showing that the model's accuracy in predicting GPS error is moderate. While it correctly predicts most true positives, there is room for improvement. The FDR is 25.60%, which is higher than for the other parameters. This suggests a higher proportion of false positives, meaning the model may be incorrectly predicting GPS error more often. With a PPV of 92.70%, the model performs the best at predicting the sprayer valve state. This very high precision indicates that the model is extremely reliable in classifying the correct valve settings. The FDR of 7.30% is the lowest among all the features, showing that the model rarely makes false positive predictions for the sprayer valve.

The model performs exceptionally well for features like Sprayer Valve and Altitude, where it achieves high precision (PPV) and low false positive rates (FDR). Wind Speed predictions are also strong but slightly lower in performance. However, the model has more difficulty predicting Drone Velocity and GPS Error, as indicated by the lower PPV and higher FDR values for these features. This suggests that further tuning or improvements in the model might be necessary for these particular aspects to enhance overall performance.

IV. Conclusion

Experiments on the Smart Sprayer system using an autonomous drone demonstrate that classifying watering strength with the weighted KNN method achieves an accuracy of 90.7%. The dataset consists of 3,750 samples, divided into five classes of 625 data points each, with an 80:20 split between training and test sets. Watering discharge strength is classified into six categories: Stop, Very Low, Low, Medium, High, and Very High. The high accuracy achieved suggests that the proposed method holds significant promise for smart sprayer systems on autonomous drones. The model also performs well on key metrics such as Precision and Recall, particularly in predicting features like Altitude and Sprayer Valve, where it exhibits high Positive Predictive Values and low False Discovery Rates. However, challenges remain in accurately classifying Drone Velocity and GPS Error, which show lower Precision and higher False Discovery Rates. To enhance performance, especially in these weaker areas, further refinement in feature differentiation and model tuning is recommended. Future research could focus on deploying the system in real agricultural environments and upgrading hardware components to further optimize performance.

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