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Enhancing Support Vector Machine Classification of Nutrient Deficiency in Rice Plants Through Particle Swarm Optimization-Based Feature Selection

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***Abstract*— The research focuses on the classification of nutrient deficiencies in rice plant leaves using a combination of Support Vector Machine (SVM) and Particle Swarm Optimization (PSO) methods for feature selection. Image features are extracted using Histogram of Oriented Gradients (HOG), which is then optimized with PSO to select the most relevant features in the classification process. Indonesia is one of the largest rice producers in the world, with food security as a major issue that requires sustainable solutions, especially in the agricultural sector. The growth and yield of rice plants are highly dependent on the availability of nutrients such as Nitrogen (N), Phosphorus (P), and Potassium (K). However, traditional observation methods to detect nutrient deficiencies in plants become inefficient as the scale of production increases. The dataset used includes images of rice leaves showing nitrogen (N), phosphorus (P), and potassium (K) deficiencies. Experiments show that the SVM model optimized with PSO provides a classification accuracy of 83.19% and a runtime of 129.63 seconds with 1150 best feature combinations out of 2303 extracted features, which is higher accuracy and faster runtime than the model that does not use PSO. These results show that the integration of PSO in the feature selection process not only improves the accuracy of the model, but also reduces the required computation time. This research makes an important contribution to the development of an automated system for the classification of nutrient deficiencies in crops, which can be implemented in large farms or other agricultural fields.**

***Index Terms*— Histogram of Oriented Gradients (HOG); Nutrient Deficiency; Particle Swarm Optimization (PSO); Rice plants; Support Vector Machine (SVM).**

I. INTRODUCTION

Rice is the staple food for more than half of the world's population, so it is very important for food security [1]. According to USDA (U.S Department of Agriculture) Foreign Agricultural Service on Rice-USDA-Foreign-Agricultural-Service (fas.usda.gov), Indonesia is the 4th largest rice producer in the world with a total production of 33 million tons in 2023. With an area of only 7% of Indonesia's land area, Java Island is still the largest contributor to rice production, reaching 53% of the total national rice production [1].

Food security implies that people can consume the ingredients they need for an active and healthy lifestyle at any time, in any quantity or variety. In this context, “food security” is usually considered, meaning when it is physically and economically feasible to use. In terms of physical availability of food, it is natural to consider the amount and variety of food products that meet effective demand in their area of demand. This refers to the food supply of a region or the food supply of a country [2].

To meet the needs of a growing population along with the depletion of food supplies, the world faces a number of serious problems related to the availability of sufficient food in a sustainable way [3]. Food security, quality food production and increasing crop yields are major global challenges in the agricultural sector. Plant growth or yield is highly dependent on several nutrients. Nutrients are essential for overall plant growth and development [4].

Since long after primitive agriculture emerged, field observation has been a common method for monitoring crop growth and identifying plant diseases. However, with the tremendous increase in crop yields, traditional observation methods are inefficient for systematic management and assessment. Meanwhile, aberrations arise when the eyes can hardly distinguish a series of similar crop symptoms [5]. Moreover, inspecting long fields or crops can be tiring and demand a lot of effort. Therefore, an automated mechanism is needed to detect nutrient-deficient vascular plants in a precise and timely manner. Image-based plant nutrient deficiency identification is a promising and efficient solution as it is a non-invasive, efficient, and accurate method that can be applied in large fields [4].

Given the rapid development of artificial intelligence (AI) such as Machine Learning that can provide innovative solutions to increase rice production, the main source of food for more than half of the world's population. By utilizing it to detect nutrient deficiencies in rice plants quickly and accurately, food security challenges can be addressed more effectively, supporting the sustainability of rice production amidst limited resources and increasing global demand. This research aims to classify nutrient deficiencies in rice plant leaves using image processing and machine learning techniques. Machine learning in agriculture is not new, and several machine learning approaches have been implemented to support agricultural processes, control, or monitoring [6]. Our research will focus on nutrient deficiencies of Nitrogen (N), Phosphorus (P), and Kalium or the same as Potassium (K). The most important nutrients for plants are Nitrogen (N), Phosphorus (P), and Potassium (K). Some specific changes appear in rice leaves due to loss of mineral balance. The scarcity of macronutrients, especially nitrogen, phosphorus and potassium in rice, can result in obvious symptoms [7].

There are several previous studies related to similar problems or related to the classification of nutrient deficiencies in crops or harvests using various machine learning and deep learning. The Support Vector Machine (SVM) method is able to efficiently find the ideal combination of classification bands while maintaining excellent classification accuracy, as shown by Juan W's experiments [8], [9]. Especially in image classification, SVM has the highest performance compared to other machine learning models such as, K-Nearest Neighbor (KNN), Naïve Bayes (NB), Binary Decision Tree (BDT) and Discriminant Analysis (DA) [10]. Research on the classification of nutritional deficiencies in corn plant leaves using the SVM model and achieved 80% accuracy [11]. Classification of nutritional deficiencies in chili plants using the SVM model without feature extraction and achieved 84% accuracy [12].

Some research related methods researchers use Deep Learning, namely, Convolutional Neural Network (CNN). CNN is one of the best image processing approaches in Artificial Intelligence that implements general and detailed tasks [13]. The accuracy of related researches get a high accuracy score in the range of 85% - 99 [4], [5], [6], [14], [15], [16]. Unfortunately, one of the disadvantages of CNN models is that they usually require large datasets to train a decent model [8], [9], [17]. SVM has higher accuracy when testing small datasets. Small data will result in a high difference in training and testing accuracy so that the model will experience overfitting problems [18]. In addition, the time required for testing is also faster than CNN [8], [9], [19].

Some studies use similar Machine Learning models, namely, Support Vector Machine (SVM) assisted with feature extraction such as Histogram Oriented Gradients (HOG) but unfortunately do not use optimization methods such as Particle Swarm Optimization (PSO) which can select features to improve classification performance.

Research by Zhe Xu et al. on a similar problem used the SVM model and HOG extraction features and got a classification accuracy of 56.86%. The accuracy is relatively low due to weaknesses, among others, not using the PSO optimization method [20]. Research by Prabira Kumar et al. on the lack of Nitrogen elements in rice plants that use SVM models and HOG extraction features and get classification accuracy at 55.30% [14]. Just like previous studies, this study did not use PSO optimization methods that could improve model performance. Investigation of machine learning and deep learning models to classify potassium and healthy leaves from grapevine. Researchers used HOG and Principal Component Analysis (PCA) to reduce features and then input to SVM and achieved 66.70% classification accuracy [21]. The weakness of the model could be due to the use of PCA which is less optimal than the PSO method.

Compared to other feature selection methods, the PSO-SVM method simplifies feature selection and effectively reduces the required parameters, resulting in higher classification accuracy most of the time [22]. PSO method is proven to be more effective than other optimization methods such as PCA, especially in improving classification performance in the SVM algorithm. The advantage of PSO lies in its ability to perform better global exploration in the solution space, resulting in more optimal SVM parameters than other optimization methods. Therefore, we conducted research using SVM model with HOG extraction features complemented by PSO method.

In previous research, image classification models using Support Vector Machine (SVM) with Histogram Oriented Gradients (HOG) extraction and Particle Swarm Optimization (PSO) methods were rarely used. Being the right target to achieve a goal by using the HOG feature extraction method and PSO feature selection to select the best features based on a collection of particles. This method is considered suitable to be applied because it aims to achieve a higher level of accuracy more efficiently. Comparing the classification results of nutrient deficiency images on rice plants shows the contributions of this research: (1) testing the effect of PSO method on SVM classification model; (2) investigating the relationship between PSO method and HOG feature extraction; and (3) finding solutions and combinations of selected features to achieve accurate performance of nutrient deficiency image classification in rice plants.

This document is organized in 4 chapters: chapter 1 discusses the background of the research, chapter 2 discusses the model and method of our research, chapter 3 describes the evaluation details and experimental results, and chapter 4 describes the conclusion of the research.

II. METHOD

A. Research Design

The study aims to measure the success rate of the combination of the Support Vector Machine (SVM) model with Histogram of Oriented Gradients (HOG) feature extraction and the Particle Swarm Optimizations (PSO) feature optimization method in classifying rice plants that are deficient in Nitrogen, Phosphorus, and Potassium nutrients based on the accuracy rate while getting the best combination of features. HOG extracts features from each image in the dataset and then selects the best features by PSO to be input to the SVM model as classification training material.

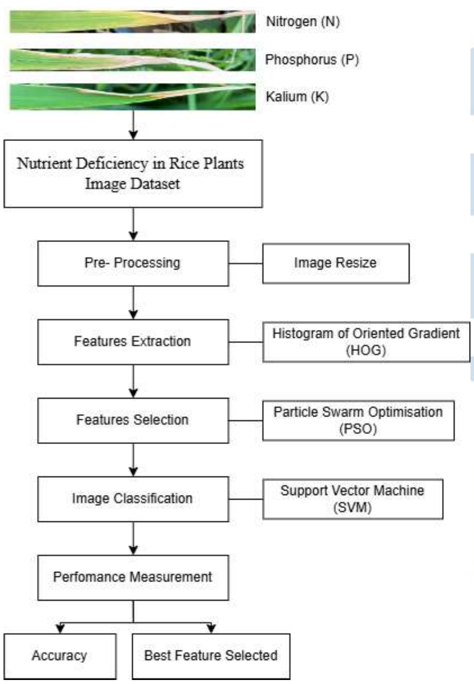

Fig. 1. Research design diagram

Based on Figure 1, the classification process begins by dividing the Nutrient Deficiency in Rice Plants dataset into 70% training data, 20% validation data, and 10% testing data. The images from the dataset were resized to 1024x256 pixels using cv2 to save resources. After that, image features were extracted using the HOG method with parameters of 9x9 pixels per cell, 2x2 cells per block, and 9 directions in the orientation histogram, then normalized with L2-Hys norm before proceeding to feature selection by PSO.

Feature selection is performed using the PSO method with 5 epochs, pop size up to 25, and perturbation rate 0.05 to get the best feature combination. The best feature combination was then used to train the RBF kernel-based SVM model with parameters C = 10.0 and gamma = 'scale'. Proper parameter adjustment will allow the SVM to find better classification hyper-fields, thereby improving classification accuracy [22].

Performance evaluation is done by comparing the accuracy values on the tested datasets, and the classification results, including the selected feature combinations and model performance, are saved in an Excel file for further analysis. PSO-SVM can be an ideal pre-processing tool to help optimize the feature selection or classification process as it can improve classification accuracy while keeping the required computational resources to a minimum [22].

B. Data Gathering and Preparation

In this research, two initial stages were carried out, namely data collection and processing to prepare the dataset. The dataset used in this research is an image of a rice plant that lacks Nitrogen (N), Phosphorus (P), and Potassium (P) Nutrient-Deficiency-Symptoms-in-Rice (kaggle.com). Table 1 provides the raw dataset details.

TABLE I. IMAGE DATASET DETAILS

Image Label	Image Quantity
Nitrogen (N)	440
Phosphorus (P)	383
Kalium (K)	333
Total	1156

We then divided the dataset into three parts, namely 70% training, 20% testing, and 10% validation. The training data consists of 809 images including 308 images of rice plants lacking Nitrogen, 233 images of Phosphorus deficiency, and 268 images of Potassium deficiency then the testing data consists of 232 images including 88 images of rice plants lacking Nitrogen, 67 images of Phosphorus deficiency, and 77 images of Potassium deficiency and, for validation consists of 115 images including 44 images of rice plants lacking Nitrogen, 33 images of Phosphorus deficiency, and 38 images of Potassium deficiency.

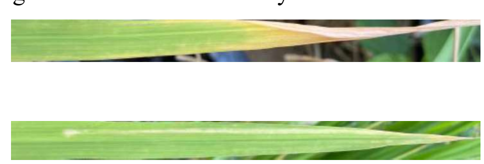

Fig. 2. Nitrogen deficiency rice plant

Fig. 3. Phosphorus deficiency rice plant

Fig. 4. Potassium deficiency rice plant

Figure 2 until 4 are examples of rice plant images from each label in the dataset. The images in the dataset are relatively large in pixel size and resolution giving a rectangular shape. Therefore, the researcher resizes the images in the dataset to 1024 x 256 to save resources and speed up the training process. When resized to 256 x 256 (square shape image), the classification accuracy becomes smaller because it does not match the basic resolution image.

The set of image data contained in the training data will be processed to obtain information on the unique characteristics of nutrient deficiencies in each rice plant. HOG feature extraction helps the process of extracting image features from the characteristics of rice plants lacking Nitrogen, Phosphorus, and Potassium nutrients and removing noise detected in the images.

C. Features Extraction

Histogram of Oriented Gradients (HOG) is a method for extracting features from images to facilitate image analysis. HOG is a typical image feature that is widely used in various fields of image research [23]. HOG uses windows to generate descriptors that are local to the detected key points of the image. A window consisting of a regular square grid ($n \times n$) is centered on the key point under consideration, and for each cell in the grid, a frequency histogram is generated to describe the edge orientation distribution [24].

The process of feature extraction by HOG starts by converting the original image into a grayscale image.

$$Gray = 0.3 * R + 0.59 * G + 0.11 * B \quad (1)$$

This process involves converting a color image into a gray image, where R, G, and B represent the color components of the corresponding image positions (1). Next, the algorithm calculates the gradient of each pixel of the image separately. For each pixel (x, y) in the image, the gradient is calculated using the horizontal (Gx) and vertical (Gy) gradients, while θ(x,y) is the orientation of the gradient at that point (2), (3), (4), (5).

$$Gx = I(x+1, y) - I(x-1, y) \quad (2)$$

$$Gy = I(x, y+1) - I(x, y-1) \quad (3)$$

$$G(x, y) = \sqrt{G_x^2 + G_y^2} \quad (4)$$

$$\theta(x, y) = arctan\left(\frac{G_y}{G_x}\right) \quad (5)$$

After that, the algorithm divides the image into small unit cells with the size corresponding to `pixels_per_cell`, i.e. 9x9 pixels per cell, and calculates the directional gradient of each unit cell calculated with 9 directions. Histogram generation is performed in each unit cell based on the values of θ(x,y) in that cell.

Next, the algorithm groups each cell into blocks according to `cells_per_block = (2,2)` and the gradient histograms of the cells in the blocks are combined. The gradient histograms of the cells in a block are then normalized using the L2-Hys norm method, which can be written by a certain formula where H is the histogram of the block, and ϵ is a small value to prevent division by zero (6).

$$H_{norm} = \frac{H}{\sqrt{\|H\|_2^2 + \epsilon^2}} \quad (6)$$

The normalized histogram of each block is finally combined into one long feature matrix, which serves as the result of HOG feature extraction [23].

The HOG feature matrix results will then continue the feature selection process by PSO and be inputted for the SVM model training process..

D. Features Selection

Particle Swarm Optimization (PSO) is an optimization method that selects extracted features to determine combinations as potential solutions from many available features. PSO simulates a flock of birds to describe an automatically evolving system where each candidate solution is a “flock of birds”, a particle in the search space. Each particle uses its memory and overall knowledge to find the best solution [22].

The PSO process starts with the initialization of a number of particles based on the population size (pop_size). Each particle has a random position in the search space bounded by bounds that define the range of values of each feature in the solution. Each particle also has an initial velocity that will be changed at each iteration.

Furthermore, at each iteration or epoch, each particle will be evaluated using an objective function. This objective function measures the accuracy of the SVM classification model on the validation data based on the features selected by the particle position. In our study, a feature will be selected if the solution of the feature is greater than 0.5. This accuracy is then used to determine whether the solution generated by the particle is the best so far, both individually (for the particle itself) and globally (for the entire particle population).

After evaluation, the velocity and position of each particle is updated using the formula below (7), (8). The new velocity is calculated based on a combination of the previous velocity, the particle's distance from its own best position, and the particle's distance from the best position of the entire population. Random factors (r1 and r2) and acceleration coefficients (c1 and c2) are used in this update to ensure balanced exploration of the search space. The new position of the particle is then obtained by adding this new velocity to the current position. The following is the formula for updating particle velocity and particle position:

$$v_i^{t+1} = w * v_i^t + c_1 * r_1 * (c - x_i^t) + c_2 * r_2 * (g^{best} - x_i^t) \quad (7)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (8)$$

Table 2 shows the description of the symbols in the PSO formulas that are displayed (7), (8).

TABLE II. PSO EQUATION DESCRIPTION

Symbol	Explanation
v_i^t	Velocity of the i particle at the t iteration
x_i^t	The position of the i particle at iteration t
p_i^{best}	The best position ever reached by particle i
g^{best}	The best position ever achieved by the entire population
w	An inertia factor that controls how much the particle maintains its previous velocity
c_1 dan c_2	An acceleration coefficient that controls how much the particle is attracted to the local and global best solutions
r_1 dan r_2	A random number between 0 and 1

This update process is repeated until the specified number of iterations is reached. Whenever a better solution is found, either by an individual particle or by the entire population, it is saved.

Once all iterations are complete, the best solution found throughout the process is considered the final result. This solution is then used to measure the performance of the model on the test set, with the aim of validating how well the features selected by PSO improve the accuracy of the classification model [25].

The output of the PSO process produces positions, velocities, and fitness. Positions are particle positions that indicate potential solutions to the search space, and each position element indicates whether a particular feature was selected in the classification model. Velocities are velocities that determine the change in particle position per iteration influenced by the best solution found by the particle and the population as a whole. Fitness is an assessment of solution quality based on model accuracy, and PSO aims to steer particles to the best solution to maximize fitness value.

E. SVM Classification Model

Support Vector Machine (SVM) is considered as one of the efficient machine learning methods developed based on statistical learning theory [26]. SVM, which is a supervised learning algorithm, generates decision boundaries to separate the n-dimensional space into classes [15].

SVM performs classification by transforming the original training data into a multidimensional space and constructing a hyper-plane in a higher dimension.

One of the best concepts used in SVM is the kernel function. The kernel function is a solid mathematical method used for nonlinear mapping for high-dimensional data. Through this SVM can solve the higher dimensional classification of the initial input data space set. In general, this function calculates the dot product value that maps the data points into the feature space [27].

There are several kernel options that can be used in SVM models such as, Linear, Polynomial, Radial Basis Kernel (RBF), and Sigmoid. In this study, we use the RBF kernel. Radial basis kernel functions are widely used with SVM because they select a smooth solution [27]. Radial basis kernel functions are widely used because of their strong classification ability [Pin Wang]. The following is an explanation of the RBF kernel formula used in the SVM formula:

$$K(\chi, \chi_i) = \exp\left(-\frac{\|\chi_i - \chi\|^2}{\sigma^2}\right) \quad (9)$$

When choosing RBF as a kernel there are two parameters to optimize: the penalty factor C and the RBF parameter σ (sigma), where σ is a constant to adjust the width of the Gaussian function of the kernel that must be optimized to ensure the SVM classification model runs optimally [28]. There is also a parameter γ (gamma) that can be used directly in the RBF kernel formula, where γ determines how much influence a single data point has. The relationship between γ and σ is shown (10).

$$\gamma = \frac{1}{2\sigma^2} \quad (10)$$

Then from the relationship between the 2 parameters above, the RBF kernel formula is produced in (11).

$$K(\chi, \chi_i) = e^{-\gamma x - x_i^2} \gamma > 0 \quad (11)$$

The C parameter in the SVM researcher is 10.0 and γ is 'scale' which means that the gamma value is calculated based on the number of features and data variability. An SVM model equation formula is obtained as shown (12).

$$f(x) = sign(\textstyle\sum_{i=1}^{n} \alpha_i \, y_i K(\chi_i \chi) + b) \quad (12)$$

Table 3 shows the description of the symbols in the SVM formulas that are displayed (9), (10), (11), (12).

TABLE III. SVM EQUATION DESCRIPTION

Symbol	Explanation
e	The basis of the exponential function e^x
exp(x)	Notation for the exponential function e^x
$sign$	The sign function, which returns +1 if the argument is positive and -1 if the argument is negative. It specifies the class label of x
$\sum_{i=1}^{n} \alpha_i$	Indicates that the sum is taken of all support vectors i from 1 to n. α_i is the Lagrange multiplier, which is a coefficient determined during SVM training. This coefficient is non-zero only for the support vector
y_i	The actual class label of the training sample, which can be +1 or -1
$K(\chi_i \chi)$	The kernel function, which calculates the similarity between input x and each support vector χ_i. The kernel function allows SVMs to work in a high-dimensional feature space.
χ_i	The support vector of the training data, which is the critical data point that lies closest to the decision boundary.
b	The bias term, which shifts the decision boundary.

F. Performance Measurement

Measurement of accuracy results using the Support Vector Machine (SVM) model with a dataset division of 70% training data and 30% testing data. The evaluation results of the classification are in the form of the final accuracy value and the best feature combination obtained based on feature selection in the PSO method. The following is the formula for calculating the final accuracy (13).

$$Accuracy = \frac{y_{pred}}{y_{true}} \times 100 \qquad (13)$$

The selected column indicates which features have been selected by the PSO algorithm to train the classifier. "Total Features" is the number of features selected (14).

$$Total\ Features = Number\ of\ Columns$$
$$where\ Solution >= 0.5 \qquad (14)$$

The classification process of images of rice plants that lack Nitrogen, Phosphorus, and Potassium using the Support Vector Machine (SVM) model with HOG feature extraction and PSO feature optimization method produces an accuracy value of 83.19%. PSO helps select features to get the best combination of features and get the best 1150 features from 2303 features based on the highest accuracy obtained.

III. RESULT AND DISCUSSION

This chapter will explain the results and analysis of each stage starting from feature extraction by HOG, feature selection by PSO, and accuracy performance results obtained by researchers.

A. Result of HOG Features Extraction

Histogram Oriented of Gradients (HOG) Feature Extraction successfully performed the feature extraction process from 115 rice plant images and obtained a total of 2304 extracted features. As shown in Table 4.

TABLE IV. FEATURES EXTRACTION RESULT

No. Data	X0	X1	X2	X3	X4	…	X2303
1	0.0962	0.0534	0.2108	0.3646	0.3646	…	0.0001
2	0.0739	0.0539	0.0637	0.2451	0.3536	…	0.0337
3	0.2805	0.1308	0.1038	0.0610	0.0540	…	0.0368
4	0.2805	0.1308	0.1038	0.0622	0.0718	…	0.0368
5	0.2805	0.1308	0.1038	0.0490	0.4410	…	0.0368
…	…	…	…	…	…	…	…
115	0.0954	0.0600	0.0930	0.2690	0.3153	…	0.0053

The PSO feature optimization method will help perform the feature selection process to find the best combination of features based on the selected solution. PSO utilizes the relationship between particle positions to find the best fitness value, where the fitness value of the current position will be compared with the personal best (pbest) value obtained in each iteration.

B. Result of PSO Features Selection

PSO is an optimization method that functions to select features that can improve the performance and efficiency of the classification model. We ran the process through 5 epoch iterations and a pop size of 25.

1) Features Selected

The results showed that with 1150 best feature combinations gave the highest testing accuracy at 83.19% with validation accuracy at 88.71% at epoch 1 and pop size 25.

After passing the feature selection through the PSO optimization method, for example, one of the best feature selection results is that 1150 features are obtained, which means that some of the previously extracted feature columns have been removed and Table 5 shows the following feature selection results that are obtained.

TABLE V. FEATURES SELECTION RESULT

No. Data	X0	X2	X3	X4	X5	…	X2303
1	0.0962	0.2108	0.3646	0.3646	0.0971	…	0.0001
2	0.0739	0.0637	0.2451	0.3536	0.2735	…	0.0337
3	0.2805	0.1038	0.0610	0.0540	0.0480	…	0.0368
4	0.2805	0.1038	0.0622	0.0718	0.0566	…	0.0368
5	0.2805	0.1038	0.0490	0.4410	0.3699	…	0.0368
…	…	…	…	…	…	…	…
115	0.0954	0.0930	0.2690	0.3153	0.2539	…	0.0053

With a combination of selected features, namely [0, 2, 3, 4, 5, 7, 9, 12, 14, 15, ..., 2287, 2288, 2289, 2290, 2291, 2292, 2293, 2294, 2298, 2303] which means there are 1153 features removed.

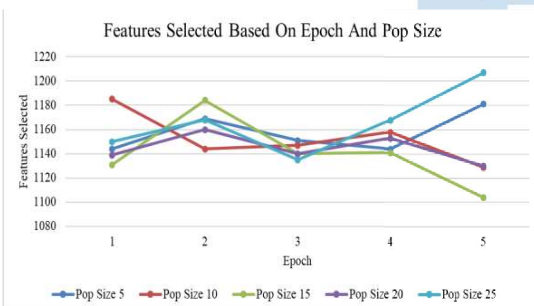

Fig. 5. Features selected comparison by epoch and pop size

As illustrated in Figure 5, epoch and pop size do not have a significant effect on the selected features, but the effect varies. The smallest combination of features is also obtained at 1104 at epoch 5 and pop size 15, while the largest combination of features is 1207 at epoch 5 pop size 25. Epoch 1 to Epoch 5 show an average number of selected features from 1142.6 to 1150.2, with a relatively large variance from 40.3 to 1791.7. Higher epochs do not always result in more features being selected, for example, epoch 3 has the fewest features with high stability and more stable variance.

Pop Size 5 to Pop Size 25 shows an average number of selected features from 1140 to 1165.6, with variance from 143.3 to 828.5. Larger pop sizes tend to produce more selected features, but with higher variance and show stability in feature selection as the pop size increases.

Based on the ANOVA results, the epoch factor has an F value of 0.642 and a P-value of 0.641. The F value is below the crit F value of 3.007 and the P-value is far above 0.05 as a general significance standard. Then the pop size factor has an F value of 1.014 and a P-value of 0.429. The F value is below the F crit value of 3.007 and the P-value is above 0.05. Based on the values of the ANOVA results, it shows that the variance of 5 epochs and pop size 5 to 25 does not have a significant effect or change on the number of features selected in the PSO method.

2) Solution Particle Movement

The solution row generated from each experiment is the position of a particle in the search space describing potential solutions that are updated continuously based on the particle's personal experience and information from other particles in the swarm.

For example, the following best solutions were obtained based on the highest testing accuracy of 83.19% at epoch 1 and pop size 25, namely [0.586, 0.491, 0.666, 0.832, 0.740, ... , 0.919, 0.582, 0.647, 0.368, 0.242].

The particle position range is from 0.0003 to 0.999 which covers almost the entire range from 0 to 1. The mean particle position result of 0.499 shows the particle positions tend to be evenly distributed around the center point which means the exploration is not significant towards either side of the space. The standard deviation of 0.266 indicates there is considerable variation in particle positions around the mean. Most of the particles are in the range of 0.233 to 0.765 indicating the particle positions are widely spread in the search space and PSO is still actively moving in search of the best solution and PSO is not trapped in a local solution.

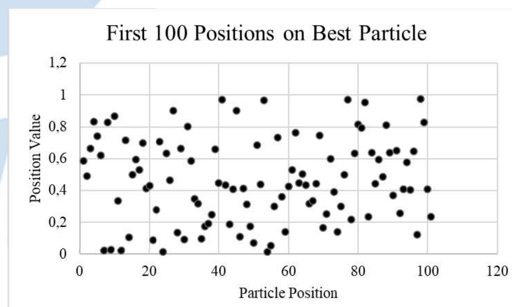

Fig. 6. 100 position changes on best particle

The scatter plot in Figure 6 is an illustration of the best particle position which contains the distribution of the first 100 positions on the particle. The distribution of the particle position points is quite even and shows that the particle explores quite widely in the search space, trying various positions to find the optimal solution.

As explained earlier, the particle movement is constantly changing without any initial convergence to a particular position. Some position points are more often in the range 0.4 to 0.8, but the points in this range are not very concentrated. This suggests that the particles often find better fitness values in the middle of the range, while still exploring the entire range.

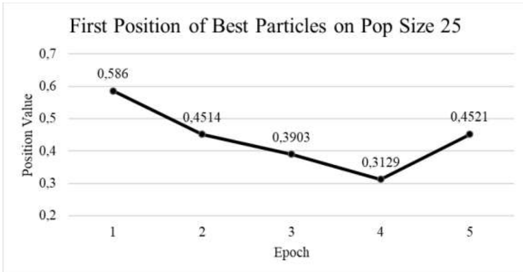

Fig. 7. First position changes on each epoch and pop size 25

Researchers analyzed the movement of the first position of each best particle in each epoch with a pop size of 25 in the first position as shown in Figure 7.

It is known that at epoch 1 the best testing accuracy is obtained so that it can be said that the initial position value of 0.586 is better than in the following epochs. From epoch 2 then there is a decrease until epoch 4 with a position value of 0.313 and the difference is 0.273. The decrease indicates that the particle explores but does not provide an increase in accuracy compared to epoch 1. Then there is an increase to epoch 5 with a position value of 0.452 which indicates that the algorithm tries to return to an area closer to the optimal position at epoch 1.

3) Velocities

The velocities line shows the speed of the particles in making movements to change position and explore for optimal solutions.

For example, the best velocities are obtained as follows based on the highest testing accuracy of 83.19% at epoch 1 and pop size 25, namely [1.588, -0.494, -0.229, 0.652, 0.175, ... , 0.223, 0.048, 0.087, -0.124, -0.544].

The range of particle velocities is from -1.992 to 1.927 indicating that particles can move quickly, either towards a better position or away from the optimal position. The mean value of 0.003 indicates that the particle displacement generally hovers around 0, indicating that the system is in a state of balance or convergence. The standard deviation of 0.496 indicates that there is considerable variation in the particle velocity which means that the actual velocity of the particles varies considerably even though the average is close to zero.

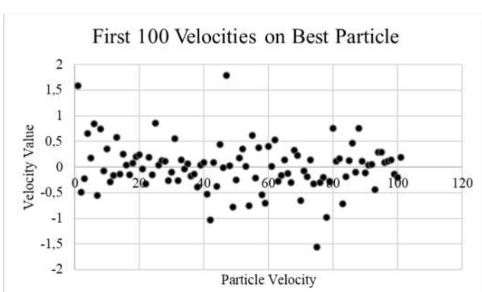

Fig. 8. 100 velocity changes on best particle

The scatter plot in Figure 8 is an illustration of the velocity at the best position which contains the distribution of the first 100 velocities on the particle. The distribution of particle velocity points with a range from about -2 to 2 however, looks symmetrical around zero which indicates the particle velocity changes in both directions (positive and negative).

As explained earlier, the distribution of velocity changes is symmetrical around zero with high variability and gets sparser as it moves away from zero indicating the particle velocity tends to be close to a normal distribution.

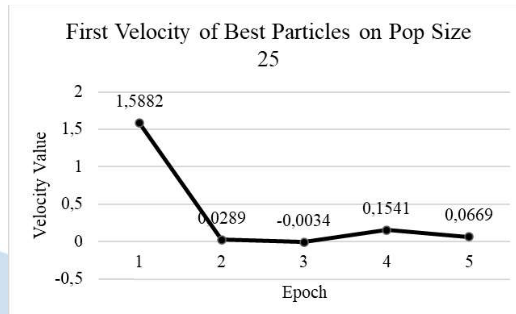

Fig. 9. First velocity changes on each epoch and pop size 25

Researchers analyzed the first speed of each best particle in each epoch with a pop size of 25 in the first position as shown in Figure 9.

Obtaining the best testing accuracy at epoch 1 with a speed value of 1.558 shows that a wide and fast initial exploration helps particles find the optimal solution. The drastic change in epoch 2 at 0.029 shows that the best particle experienced a very significant decrease in velocity after epoch 1. This indicates the system's efforts to reduce exploration and focus on exploitation. The velocity change from epoch 2 to epoch 5 becomes smaller and more stable, this change leads to the stability of the best particle velocity in the next few epochs. The change from a negative value at epoch 3 of -0.003 to a positive value at epoch 4 of 0.154 indicates that the best particle may be adjusting its position to stay around a more optimal solution.

C. Classification Accuracy

Researchers get the highest validation accuracy of 90.00% at epoch 2 and pop size 10, while the lowest is 85.22% at epoch 1 pop size 5 as depicted in Figure 10.

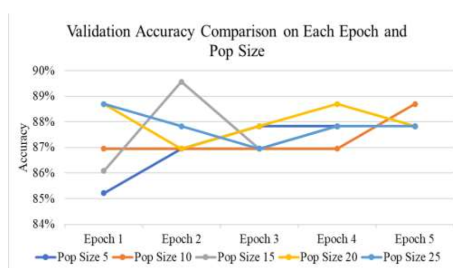

Fig. 10. Validation accuracy comparison by every epoch and pop size

The average validation accuracy between epochs has a range from 87.13% to 87.83%, indicating that epoch changes have a relatively small effect on validation accuracy. The smallest variance at epoch 5 and the largest at epoch 1 indicates epoch 5 is more stable than epoch 1.

The average validation accuracy at various population sizes ranges from 87.65% at pop size 15 to 87.83% at pop size 25. Populations of size 25 tend to give slightly better results in validation accuracy. The variance of pop size 15 is lower than the variance of pop size 20, indicating that pop size 15 has the best stability.

Based on the evaluation of validation accuracy analysis results using Analysis of Variance (ANOVA). The epoch and pop size factors show all ANOVA results have the same value, namely the F value at 0.683 and the P-value at 0.614. The F value is less than the crit F value of 3.007 and the P-value is also greater than 0.05 as the general level of significance. Based on the values of the ANOVA results, it shows that the variance of 5 epochs and pop size 5 to 25 does not have a significant effect or change on the validation accuracy of the classification model for nutrient deficiencies in rice plants.

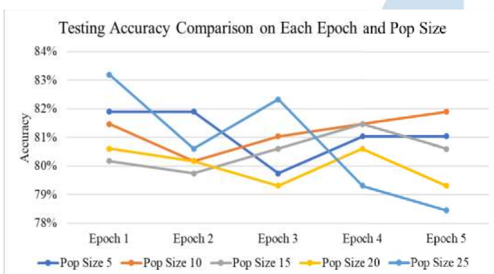

Fig. 11. Testing accuracy comparison by every epoch and pop size

As depicted in Figure 11, researchers got the highest testing accuracy of 83.19% at epoch 1 and pop size 25 and the lowest testing of 78.45% at epoch 5 and pop size 25.

The average testing accuracy has a range of 80.26% at epoch 5 to 81.47% at epoch 1. Epoch 1 has the highest average accuracy, while epoch 5 has the lowest accuracy. The variance of accuracy between epochs appears to be quite low, ranging from 6.8E-05 in epoch 2 to 0.0002 in epoch 5. This shows that epoch does not significantly affect testing accuracy.

The average testing accuracy based on pop size ranges from 80.52% at pop size 15 to 81.21% at pop size 5. Pop size 5 shows the highest testing accuracy results compared to other pop sizes. The lowest variance for pop size is 4.1E-05 in pop size 15, while the highest is 0.0004, which indicates that the testing accuracy at pop size 15 is more consistent than other pop sizes.

Based on the results of ANOVA analysis related to accuracy testing data, the epoch factor obtained a P-value of 0.525 and an F value of 0.832. The F value is still far below the F crit value of 3.007 and the P value is far above 0.05 as the general significance level. The pop size factor also shows a P-value of 0.453 and an F-value of 0.966. The F value is still far below the F crit value of 3.007 and the P value is far above 0.05. Based on the values of the ANOVA results, it can be concluded that the variance of 5 epochs and pop size 5 to 25 does not have a significant effect or change on the accuracy of validation of the classification model for nutrient deficiencies in rice plants.

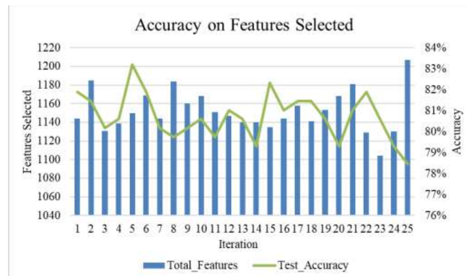

Fig. 12. Accuracy comparison by features selected

Figure 12 shows the movement of the selected features and the accuracy obtained during 25 iterations of the experiment. The highest accuracy is 83.19% when the features are selected at 1150 and the lowest accuracy is 78.45% when the features are selected at 1207. The number of selected features fluctuated in each iteration from 1104 to 1207 with an accuracy range of , but did not show any drastic changes. The total number of features does not directly affect the accuracy obtained, there is no linear or consistent pattern as the number of selected features changes.

Researchers analyzed the relationship between the number of selected features and accuracy results. An ANOVA analysis of the relationship between the two was conducted, resulting in a P-value of 6.22007E-43 which is far below 0.05 and an F-value of 67793.77 which is far above the F crit of 4.259. From these values, it can be concluded that the change in the number of features is highly related and significantly affects the accuracy value.

D. Runtime Result

Every experiment carried out in each epoch along with the pop size will definitely take time, the following describes the time required in each epoch.

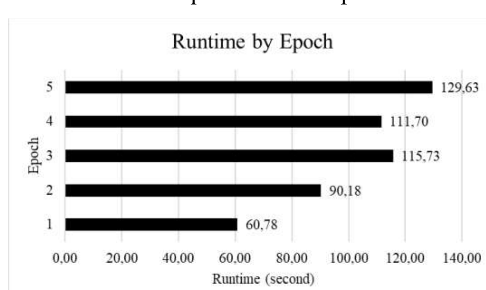

Fig. 13. Runtime comparison by epoch

As shown in Figure 13, the fastest runtime is 60.78 seconds at epoch 1 and the longest is 129.63 seconds at epoch 5. It can be concluded that the runtime tends to increase at each epoch. This can be caused by several factors ranging from the complexity of the model that increases with increasing epochs, the amount of data processed, and the PSO algorithm adjustment process.

E. Result Comparison

Researchers conducted non-PSO experiments on the same dataset using the same SVM classification model without using HOG extraction features or PSO selection features. The accuracy was 73.04% with a runtime of 540 seconds.

PSO model accuracy increases the accuracy of the model to 83.19% and the runtime is only 129 seconds. There was an increase in accuracy of 10.15% and a faster runtime of 411 seconds compared to the non-PSO model.

Therefore, it can be concluded that the PSO optimization method as a selection feature provides improved classification performance in terms of accuracy and runtime.

IV. Conclusion

This research aims to improve the accuracy of nutrient deficiency image classification in rice plants by combining Particle Swarm Optimization (PSO) and Histogram of Oriented Gradients (HOG) using the Support Vector Machine (SVM) classification model. The integration of PSO in the feature selection process was shown to significantly improve the accuracy and efficiency of the SVM classification model. The final model achieved an accuracy of 83.19% and a runtime of 129.63 seconds with 1150 best feature combinations out of 2303 extracted features. The study showed significant improvement compared to the model that did not use PSO. For further research, it is recommended to expand the dataset, incorporate other optimization methods, and explore other feature extraction methods and classification techniques can also be considered to improve the performance and wider application of the model.

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