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Enhanced Support Vector Machine Based on Grey Wolf Optimizer for Fruits Image Classification using MPEG-7 Color and Texture Features Fusion

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Abstract: Fruit classification from images plays a pivotal role in diverse domains. Despite numerous efforts to tackle this challenge, it remains complex due to the diversity of fruit and applications. This study presents an enhanced support vector machine (SVM) based on grey wolf optimizer (GWO) for fruit image classification. GWO is used to optimize the hyperparameters of SVM and low variance feature selection threshold. The utilization of MPEG-7 visual descriptors negates the need for segmentation. The results showcase exceptional classification accuracy across Ubaya-IFDS3000, Ubaya-IFDS5000, and Supermarket produce datasets, with standout features achieving up to 99.21%, 98,28%, and 99.85% accuracies, respectively. Notably, the proposed method consistently outperforms SVM optimized with the other optimization algorithms. Further, it excels in classification accuracy when compared to previous state-of-the-art methods. This study emphasizes the importance of hyperparameter optimization using GWO and its effectiveness in fruit image classification.

Keywords: Fruit classification, Support vector machine, Hyperparameter optimization, Grey wolf optimizer.

1. Introduction

Fruit classification from images holds significant importance in various fields, such as agriculture, food industry, retail, and dietary recommendations [1, 2]. The classification of fruits from images has been the subject of extensive research by scholars. However, it remains a significant challenge due to the sheer diversity of fruit types available in the market and its wide array of application domains. With many fruit varieties and varying visual characteristics, this field of study continues to evolve, aiming to develop robust and adaptable classification systems that cater to the diverse needs of different industries and contexts [3]. Fruit classification from images is an inexpensive method compared to other approaches [4] and is an alternative to the traditional classification method [5]. Fruit classification from images can be broadly categorized into two main methods: traditional machine learning and deep learning. In the traditional machine learning approach, some features are extracted from fruit images and then used to train the machine learning model [6].

Numerous studies have employed traditional machine learning methods to classify fruits from images [1, 6-17]. This approach usually involves segmentation and feature extraction steps in the classification pipeline. Segmentation is the process of separating objects from their backgrounds, enabling subsequent analysis and recognition [18]. Various segmentation methods have been employed for fruit classification from images in some studies, including background subtraction [8, 10, 12, 16], split-and-merge [13-15, 17], GrabCut [7], and automatics thresholding [1]. Color, texture, and shape were the most used features for fruit classification from images in the traditional machine learning approach. Several studies have implemented feature and classifier fusion strategies to enhance classification accuracy, as reported in [1, 6, 9-11, 16]. In previous research, support vector machines (SVM) and artificial neural networks (ANN) have been the predominant classifiers for fruit classification from images that

Nomenclature

$\boldsymbol{F}$	Features fusion
CS	Color structure
SC	Scalable color
CL	Color layout
HT	Homogeneous texture
ET	Edge histogram
$\mathbf{x}, \mathbf{x}_i$	Feature vector
y_i	Expected output
$y(\mathbf{x})$	Predicted output
$\mathbf{w}, b$	SVM parameters
C	Regularization parameter
$K(\mathbf{x}_i, \mathbf{x}_j)$	Kernel function
$\mathbf{P}(i), \mathbf{P}_j(i)$	The position vector of grey wolf
$\widehat{\mathbf{P}}_j$	The estimation of $\mathbf{P}$
$\mathbf{P}_p(i)$	The position vector of prey
$\mathbf{A}, \mathbf{A}_j, \mathbf{C}, \mathbf{C}_j$	Coefficient vectors
a	Scalar between 0 and 2
$\mathbf{r}_1, \mathbf{r}_2$	Random vectors
$\mathbf{D}, \mathbf{D}_j$	The distance between the wolf and the prey
$f(\mathbf{P})$	Objective function
T	The threshold value of LVFS
acc_t	Classification accuracy
C_t	The number of correctly classified images
T_t	The number of images in the dataset
α_i	Dual coefficient
ξ_i	Slack variables
γ	Kernel coefficient

achieved the best performance, such as in [1, 12-17], [19-22]. Derivative-free optimization techniques, such as fitness-scaled chaotic artificial bee colony (FSCABC) [19], biogeography-based optimization (BBO) [20], and Kalman filter (KF) [21], have also been applied to train classifiers for fruit recognition from images to enhance performance, as reported in [1, 14, 15].

In the case of fruit classification from images using deep learning, previous studies can be categorized into two main approaches: building convolutional neural networks (CNN) models from scratch [22-25] and utilizing pre-trained CNN models with transfer learning strategies [24, 26-32]. Some previous studies employed several pre-trained CNN model architectures to classify fruits from images. These architectures included MobileNetV2 [27, 28], VGG-16 [24], AlexNet [26], DenseNet [29-31], ResNet [30, 31], NASNet [30], EfficientNet [30], Inception V3 [31], and MangoNet [32]. Many researchers have employed a technique known as image augmentation to achieve a well-performing CNN model during the training phase. Image augmentation involves creating variations of the training data by applying transformations like rotations, flips, and zooms to increase the diversity of training data [23, 24, 26].

In addition to selecting the appropriate classification model, the choice and tuning of hyperparameters play a crucial role in determining the model's performance. Hyperparameters are settings or configurations not learned from the data. Still, they are essential for the model's behavior, such as learning rates, batch sizes, or the number of layers in a neural network. Optimizing these hyperparameters is crucial to obtain the best model performance [33, 34]. However, in the existing literature, hyperparameter tuning has predominantly been explored in studies focusing on fruit classification from images through deep learning approach, as reported in [29-32]. Several optimization algorithms have been employed for hyperparameter tuning in deep learning models for fruit image classification. Noteworthy among them are the Aquila Optimization Algorithm (AOA) [29], Tunicate Swarm Algorithm (TSA) [31], Harris Hawks Optimization (HHO) [32], and Bayesian Optimization [30]. On the other hand, in machine learning approach, researchers have primarily focused on selecting models, feature engineering, data preprocessing, and sometimes neglecting the crucial step of fine-tuning hyperparameters.

This study proposes an enhanced SVM based on Gray Wolf Optimizer (GWO) to classify fruit from images. GWO is a nature-inspired metaheuristic algorithm based on grey wolves' hunting and social behavior. It mimics the pack's hierarchy and cooperation to find optimal solutions [35]. GWO has been effectively applied in various hyperparameter optimization tasks for traditional machine learning [36-38] and deep learning [39-41]. In this study, GWO is employed to optimize the hyperparameters of SVM and the threshold value of low variance feature selection (LVFS) to improve the accuracy of SVM in classifying fruit from images. Moving Picture Experts Group-7 (MPEG-7) visual description [42] is used as input features to SVM. Using the MPEG-7 visual descriptor, the fruit image classification process does not require preprocessing and segmentation [43].

The strong points of the proposed method are as follows:

- Using GWO for hyperparameter optimization in SVM brings an innovative dimension to fruit image classification. To the best of the Author's knowledge, GWO has never been employed to optimize the hyperparameter of SVM for fruit image classification in the literature.
- By fusing MPEG-7 color and texture features, the proposed approach revolutionizes fruit image classification, eliminating the need for preprocessing and segmentation as well as

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significantly enhancing the performance of SVM in classifying fruit images.

- Acknowledging the diverse range of fruit types, the proposed method stands out for its ability to provide accurate and adaptable classification across various fruit datasets.
- A new Indonesian fruit image dataset, called Ubaya-IFDS5000 dataset, is also proposed in this paper.

The rest of the paper is organized as follows. In Section 2, the focus is on the materials used and the proposed method. Section 3 unfolds the outcomes of experiments, presenting a meticulous analysis of the results obtained. Finally, Section 4 encapsulates the essence of the study, synthesizing the key takeaways and implications drawn from the study.

2. Materials and methods

2.1 Ubaya-IFDS3000 dataset

The Ubaya-IFDS3000 dataset [6] is the first image dataset used in this study. The dataset has 15 classes of Indonesian fruits, namely ambarella, avocado, dragon fruit, duku, durian, guava, mangosteen, pacitan orange, persimmon, pineapple, salak, sapodilla, siam lime, soursop, and star fruit. The dataset contains a total of 3000 images, with 200 images per class. All images were captured using a Canon EOS Kiss X6i camera in RGB (Red, Green, Blue) color space, with a dimension of 2592×1456 pixels and a resolution of 72 dpi and saved as a JPEG file. The dataset incorporated five background colors (pink, white, light blue, light green, and light yellow) and two illumination levels (160 and 1050 lumens). Images were taken with the camera tilted at 0^o or 45^o to introduce variance. Deliberate choices such as varying object counts and shadows enhanced dataset complexity. Fig. 1 displays some fruit images from the Ubaya-IFDS3000 dataset.

Figure. 1 Some fruit images in Ubaya-IFDS3000 dataset

Figure. 2 Some fruit images in Ubaya-IFDS5000 dataset

2.2 Ubaya-IFDS5000 dataset

This study introduces Ubaya-IFDS5000, a novel Indonesian fruit image dataset, serving as the second dataset. Comprising 25 diverse Indonesian fruits, including ana apple, bilimbi, cantaloupe, cucumber, green water apple, cashew, star apple, long watermelon, manalagi apple, matoa, melon, mulberry, palmyra palm fruit, papaya, passion fruit, pomegranate, pomelo, rambutan, strawberry, sugar apple, timun krai, timun suri, tomato, watermelon, and watery rose apple. the dataset was sourced from traditional markets in Surabaya and Sidoarjo, East Java, Indonesia. All images were acquired using the same setup as in Ubaya-IFDS3000 dataset. The dataset contained a total of 5000 images, with 200 images per class. A Canon EOS 80D camera was used to capture all images in RGB color space, with a dimension of 2976×1984 pixels and a resolution of 72 dpi and saved as a JPEG file. Some images from the Ubaya-IFDS5000 can be seen in Fig. 2.

2.3 Supermarket produce dataset

Supermarket produce dataset [10] is the third image dataset used in this study. The dataset consists of 15 classes of fruits and vegetables, including agata potato, asterix potato, cashew, diamond peach, fuji apple, granny smith apple, honeydew melon, kiwi, nectarine, onion, orange, plum, spanish pear, taiti lime, and watermelon, as shown in Fig. 3. This dataset has a total of 2633 images with 75 to 264 images per class. Each image was captured on a white or clear background using a Canon PowerShot P1 camera with the dimension of 1024×768 pixels in RGB color space. The illumination of each image in the dataset was different when it is recorded. Each image in the dataset contains a different number of objects. The dataset contained images in diverse

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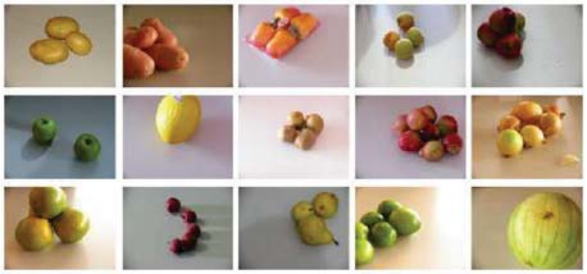

Figure. 3 Some fruit and vegetable images from Supermarket produce dataset

poses, some with objects enclosed in plastic bags, intensifying specular reflection. Shadows and partially obscured objects, adding realism, were deliberately included in the dataset.

2.4 Feature extraction

In this study, five MPEG-7 color and texture features, namely color layout (CL), color structure (CS), scalable color (SC), edge histogram (EH), and homogeneous texture (HT), were directly acquired from the whole pixels in each fruit image. No preprocessing or segmentation steps were used in the extraction of these features. The color feature is selected as the one to use since it is a visual feature frequently utilized in object recognition. Additionally, color is resistant to being translated, rotated, and viewed from different angles. On the other hand, texture not only contains the structural information of the surface but also conveys the visual pattern of the surface [42].

Color layout refers to how colors are distributed over an image in the spatial domain. It is extracted in the YCbCr color space. Firstly, the image is divided into 64 equal blocks to ensure resolution invariance. The averages of pixel intensities in each channel are calculated as representative colors from each block to produce three 8×8 tiny images. The tiny images were transformed into frequency domain using discrete cosine Fourier transform (DCT). A zigzag scanning is carried out to select the first few DCT coefficients. The chosen coefficients are then subjected to a nonlinear quantization process to produce color layout features having a length of 120, 64 from the Y channel, 28 from the Cb channel, and 28 from the Cr channel.

The color structure of an image is an expression of the spatial color structure present in a particular location as well as the overall color distribution of the image. The spatial color structure information makes the feature sensitive to the specific image characteristics that are not visible by employing an ordinary color histogram. This feature is obtained in HMMD color space. The entire image is scanned with an 8×8 structuring element to produce a 256-bin histogram. The value of each bin is updated at each place in the image by counting the number of occurrences of a particular color within the structuring element.

Scalable color is extracted in HSV color space by constructing a 256 bins color histogram. The color space is uniformly quantized to 256 colors consisting of 16 levels H channels, four S channels, and four V channels. The histogram is normalized and then mapped into a 4-bit integer representation to give great weight to small values that occurred with a higher probability. After that, a Haar transform is applied to encode the histogram. This process is used to facilitate the scalability of the descriptor.

The spatial edge distribution of an image can be described using an edge histogram. Before the edge histogram can be extracted, the image is initially partitioned into 4×4 nonoverlapping big blocks. The edge information on each block is computed and categorized into five groups: vertical, horizontal, 45° diagonal, 135° diagonal, and isotropic. This is accomplished with the assistance of four directional selective edge detectors and one isotropic edge detector. As a result, the edge histogram feature contains five bins on each block. Therefore, there are 80 bins across the image.

The direction, hardness, and frequency of the pattern in the image can be characterized by a homogeneous texture feature. This feature is suitable for quantifying the texture of the image with a homogeneous characteristic. The 2D frequency space of the image is firstly segmented into 30 channels by five octave segments in the radial direction and six equal segments in the angle direction at the interval of 30 degrees before the homogeneous texture extraction. A Gabor-filtered Fourier transform is employed in each frequency channel. The mean energy and the deviation of energy are calculated from the filter output in each channel to produce a 60-bin histogram. The histogram is then concatenated with one bin histogram from the mean of pixel intensities and one bin histogram from the standard deviation of pixel intensities to obtain a 62-bin histogram. This study selects some fusion of MPEG-7 color and texture features according to the features used in fruit classification proposed in [9]. All fusions are tabulated in Table 1.

Table 1. The fusion of MPEG-7 color and texture features used for classification

i	Features fusion (F_i)	i	Features fusion (F_i)
1	CS	13	CS+CL+HT
2	SC	14	CS+CL+EH
3	CS+SC	15	CS+HT+EH
4	CS+CL	16	SC+CL+HT
5	CS+HT	17	SC+CL+EH
6	CS+EH	18	SC+HT+EH
7	SC+CL	19	CS+SC+CL+HT
8	SC+HT	20	CS+SC+CL+EH
9	SC+EH	21	CS+SC+HT+EH
10	CS+SC+CL	22	CS+CL+HT+EH
11	CS+SC+HT	23	SC+CL+HT+EH
12	CS+SC+EH	24	CS+SC+CL+HT+EH

2.5 Low variance features selection

The essential goals of feature selection are data cleaning, developing models that are less complicated and easier to understand, as well as improving classification accuracy. Several feature selection methods have been proposed and can be divided into four groups: statistical based, similarity based, sparse learning based, and information theoretical based. The technique applied during the feature selection process serves as the basis for this categorization [44].

Statistical based feature selection employs some statistical measures to extract the characteristics of features while selecting the important features. This method works independently from the learning algorithm. Therefore, it is more efficient compared to other methods. This study employs a simple statistical based feature selection that relies on variance, called low variance feature selection (LVFS) [44]. The importance of each feature is ranked based on its variance. A feature with a larger variance is considered more important than a feature with a smaller variance. A threshold value T needs to be determined first before feature selection. A feature with a variance less than T is considered unimportant and will be removed from the feature set. In this study, the value of T is determined using Grey Wolf Optimizer in the range [0,10], such that the best classification performance is achieved. Furthermore, this study uses the implementation of LVFS in Scikit-learn library [45] to perform feature selection.

2.6 Support vector machine

Support vector machine (SVM) is a classifier used initially for binary classification problems. Suppose the training data for the binary classification problem consists of the input feature vectors $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N$ and the corresponding expected output $y_1, y_2, \dots, y_N$, where $\mathbf{x}_i \in \mathbb{R}^m$, $y_i \in \{-1,1\}$ for $i = 1,2,\dots,N$ and N is the number of training data. SVM aims to find a hyperplane as in Eq. (1),

$$y(\mathbf{x}) = \mathbf{w}^T \phi(\mathbf{x}) + b \tag{1}$$

that can be used to classify an unknown input feature vector $\mathbf{x}$ by $\mathrm{sign}(y(\mathbf{x}))$, where $\mathbf{w} \in \mathbb{R}^m$ and $b \in \mathbb{R}$ are SVM parameters, and ϕ is a feature space mapping. The values $\mathbf{w}$ and b are determined by maximizing margin, which is the distance between $\mathbf{w}^T \phi(\mathbf{x}) + b = 0$ and the closest of the input feature vectors in training data [46].

The problem finding the optimum values of $\mathbf{w}$ and b can be formulated using the optimization problem in Eq. (2) and (3),

$$\min_{\mathbf{w},b,\xi_1,\xi_2,\dots\xi_N} \frac{1}{2}\|\mathbf{w}\| + C\sum_{i=1}^{N} \xi_i \tag{2}$$

subject to

$$y_i(\mathbf{w}^T \phi(\mathbf{x}_i) + b) \geq 1 - \xi_i, \quad \xi_i \geq 0 \tag{3}$$

where $\xi_i, i = 1,2,\dots,N$ are slack variables defined as distance between expected output y_i and predicted output $y(\mathbf{x}_i)$, and $C > 0$ is regularization parameter to control trade of between the slack variables and the margin. The above optimization problem can be formulated as dual problem as in Eq. (5) and (6),

$$\max_{\alpha_1,\alpha_2,\dots\alpha_N} \sum_{i=1}^{N} \alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_i\alpha_j\, y_i y_j K(\mathbf{x}_i, \mathbf{x}_j) \tag{5}$$

subject to

$$0 \leq \alpha_i \leq C, \sum_{i=1}^{N} \alpha_i\, y_i = 0 \tag{6}$$

where $K(\mathbf{x}_i, \mathbf{x}_j) = \phi(\mathbf{x}_i)^T \phi(\mathbf{x}_j)$ is the kernel function and $\alpha_1, \alpha_2, \dots \alpha_N$ are the dual coefficients.

SVM can be extended to the multiclass problem by combining some binary SVM classifiers using either one versus one or one versus rest approaches. This study uses a one versus one approach by contracting $k(k+1)/2$ binary SVM classifiers on all combinations of two classes. The kernel function used in this study is the radial basis function as in

$$K(\mathbf{x}, \mathbf{x}') = \exp(-\gamma\|\mathbf{x} - \mathbf{x}'\|) \tag{7}$$

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Eq. (7), where γ is a kernel coefficient. The accuracy of SVM depends on the values of hyper-parameters C and γ provided by the user. Therefore, the values of C and γ need to be optimized to obtain the best classification performance. In this study, Grey Wolf Optimizer was also employed to obtain the best values of C and γ from the range $[1,1000]$ and $[0.01,1]$, respectively. This study also used the implementation of multiclass SVM in Scikit-learn library to train the SVM model.

2.7 Grey wolf optimizer

Grey wolf optimizer (GWO) is a metaheuristic optimization algorithm that takes inspiration from grey wolves (*Canis lupus*) [35]. It works by imitating the social hierarchy and hunting strategy of grey wolves found in their natural environment. The social hierarchy is simulated using four types of grey: alpha, beta, delta, and omega. The alpha wolf is the group leader who decides on prey hunting. The beta wolf is on the second level that helps the alpha wolf make decisions or do other activities. The third level is the delta wolf with the job of caretakers, hunters, elders, sentinels, and scouts. The omega wolf consisted of wolves, not in alpha, beta, and delta. In each iteration of the GWO algorithm, the best solution is modelled as the alpha wolf (α). The second and third best solutions are the beta wolf (β) and the delta wolf (δ), respectively. The remaining possible solutions are all considered to be the omega wolf (ω). $\alpha, \beta,$ and δ wolves act as guides during optimization process and their movement will be followed by ω wolves.

The GWO algorithm employs a three-step hunting strategy: searching, encircling, and attacking prey to find the best solution. Suppose $\mathbf{P}(i)$ and $\mathbf{P}_p(i)$ are the position vector of a grey wolf and the prey at i^{th} iteration. The encircling behavior of a grey wolf can be modelled using Eq. (8) - (11),

$$\mathbf{A} = 2a\mathbf{r}_1 - a \tag{8}$$

$$\mathbf{C} = 2\mathbf{r}_2 \tag{9}$$

$$\mathbf{D} = \left|\mathbf{C}.\mathbf{P}_p(i) - \mathbf{P}(i)\right| \tag{10}$$

$$\mathbf{P}(i+1) = \mathbf{P}_p(i) - \mathbf{A}.\mathbf{D} \tag{11}$$

where $\mathbf{A}$ and $\mathbf{C}$ are coefficient vectors, a is a scalar with its value linearly decreased from 2 to 0 during the iteration process, $\mathbf{r}_1, \mathbf{r}_2$ are random vectors with elements falling in the range $[0,1]$, $|\ \ |$ is the element-wise absolute value of the vector, and the dot (.) operator is the element-wise vector multiplication.

The position of the best solution is unknown in the actual case. Therefore, during the hunting process, the movement of a grey wolf will be guided by $\alpha, \beta,$ and δ wolves. This condition assumes that $\alpha, \beta,$ and δ wolves have more information about the prospective prey location. Eq. (12) - (14) are used to describe the movement of the grey wolf in each iteration based on the position of $\alpha, \beta,$ and δ wolves,

$$\mathbf{D}_j = \left|\mathbf{C}_j.\mathbf{P}_j(i) - \mathbf{P}(i)\right| \tag{12}$$

$$\widehat{\mathbf{P}}_j = \mathbf{P}_j(i) - \mathbf{A}_j.\mathbf{D}_j \tag{13}$$

$$\mathbf{P}(i+1) = \tfrac{1}{3}\left(\widehat{\mathbf{P}}_\alpha + \widehat{\mathbf{P}}_\beta + \widehat{\mathbf{P}}_\delta\right) \tag{14}$$

where $\mathbf{A}_j$ and $\mathbf{C}_j$, for $j = \alpha, \beta, \delta$, are coefficient vectors as defined in Eq. (10) and Eq. (11), respectively, and $\mathbf{P}_\alpha(i)$, $\mathbf{P}_\beta(i)$, $\mathbf{P}_\delta(i)$ are the position of $\alpha, \beta,$ and δ wolves at i^{th} iteration, respectively.

In this study, GWO was used to determine the value of threshold T in LVFS and the value of hyperparameters C and γ in SVM such that the best classification accuracy of SVM can be achieved in classifying fruit images. Therefore, the position vector of a grey wolf will consist of $T, C,$ and γ, as in Eq. (15).

$$\mathbf{P} = (T, C, \gamma) \tag{15}$$

The number of grey wolf population (N) used to search for the best solution was five wolves with the maximum iteration of 10. GWO will search for the best solution $\mathbf{P}$ by maximizing classification accuracy with the objective function as in Eq. (16),

$$f(\mathbf{P}) = 1 - acc(\mathbf{P}) \tag{16}$$

where $acc(\mathbf{P})$ is the classification accuracy of SVM with $C = \mathbf{P}[2]$ and $\gamma = \mathbf{P}[3]$ and LVFS is performed with $T = \mathbf{P}[1]$.

2.8 Evaluation

Every dataset was divided into two nonoverlapping subsets with a proportion of 1:1, one for the training dataset and the remaining for the testing dataset. Stratified random sampling without replacement is employed to construct five pairs of training and testing datasets to ensure that all classes have the same proportion in both subsets.

The SVM classifier was trained using five training datasets, and the performance was evaluated using the corresponding testing data set. Five accuracies $acc_t,\ t = 1,2,3,4,5$ were calculated from five testing datasets using Eq. (16),

$$acc_t = \frac{C_t}{T_t} \times 100\% \tag{17}$$

where C_t and T_t are the number of correctly classified images and the total images in the t^{th} testing dataset, respectively. Finally, all acc_t were summarized using average to represent the performance of the SVM classifier.

3. Results and Discussion

The summary in Table 2 outlines the classification accuracy of enhanced SVM based on GWO on three datasets. The data printed in bold indicate the top three classification accuracies for each dataset. Among the feature fusions analyzed, the top three performing feature fusions in terms of classification accuracy on the Ubaya-IFDS3000 dataset are as follows. The feature fusion with the highest accuracy, securing the first and second ranks, were $\boldsymbol{F}_3$ and $\boldsymbol{F}_{10}$ with an average accuracy of 99.21%. Following closely, $\boldsymbol{F}_{11}$ claimed the third rank with average accuracies of 99.16%. These features showcase exceptional discriminative capabilities, playing a crucial role in achieving the outstanding performance of the fruit image classification model on the Ubaya-IFDS3000 dataset.

The exploration of classification accuracy within the Ubaya-IFDS5000 dataset revealed a marginally lower performance than Ubaya-IFDS3000 dataset, ranging from 94.83% to 98.29%. This disparity can be attributed to the inherent complexity and diversity present in the Ubaya-IFDS5000 dataset, potentially posing challenges for precise fruit image classification. The top three performing feature fusions regarding classification accuracy using the proposed method in Ubaya-IFDS5000 dataset are as follows. Feature fusion $\boldsymbol{F}_{19}$ stood out with an impressive average accuracy of 98.29, closely followed by $\boldsymbol{F}_{11}$ and $\boldsymbol{F}_{10}$, which exhibited notable accuracy scores of 98.18 and 97.71% respectively. These feature fusions demonstrated a remarkable ability to differentiate between the dataset's diverse fruit classes. Interestingly, as can be observed from Table 2, the feature fusions that attained the highest classification accuracy in the Ubaya-IFDS5000 dataset differ from those in the Ubaya-IFDS3000 dataset. This discrepancy shows each dataset's unique challenges and intricacies, necessitating distinct features for optimal classification performance.

Table 2. Classification accuracy of optimized SVM using GWO

$\boldsymbol{F}_i$	Average accuracy (%)		
	Ubaya-IFDS3000	**Ubaya-IFDS5000**	**Supermarket produce**
	GWO	GWO	GWO
$\boldsymbol{F}_1$	98.20	95.45	99.67
$\boldsymbol{F}_2$	98.61	96.30	99.48
$\boldsymbol{F}_3$	**99.21**	97.43	**99.82**
$\boldsymbol{F}_4$	98.19	95.64	99.65
$\boldsymbol{F}_5$	97.89	96.30	99.61
$\boldsymbol{F}_6$	97.67	95.40	99.56
$\boldsymbol{F}_7$	98.85	96.50	99.67
$\boldsymbol{F}_8$	98.60	97.47	99.68
$\boldsymbol{F}_9$	98.37	95.04	99.57
$\boldsymbol{F}_{10}$	**99.21**	**97.71**	**99.85**
$\boldsymbol{F}_{11}$	**99.16**	**98.18**	**99.77**
$\boldsymbol{F}_{12}$	98.85	96.26	99.70
$\boldsymbol{F}_{13}$	98.09	96.66	99.59
$\boldsymbol{F}_{14}$	98.08	95.45	99.53
$\boldsymbol{F}_{15}$	96.88	96.09	99.45
$\boldsymbol{F}_{16}$	99.03	97.69	99.64
$\boldsymbol{F}_{17}$	98.55	94.83	99.64
$\boldsymbol{F}_{18}$	98.45	96.87	99.61
$\boldsymbol{F}_{19}$	99.15	**98.29**	99.76
$\boldsymbol{F}_{20}$	98.77	96.90	99.70
$\boldsymbol{F}_{21}$	98.89	97.51	99.71
$\boldsymbol{F}_{22}$	97.21	96.05	99.53
$\boldsymbol{F}_{23}$	98.59	97.11	99.61
$\boldsymbol{F}_{24}$	98.80	97.60	99.68

The classification accuracy results on the Supermarket produce dataset exhibited a remarkable level of performance, surpassing the outcomes observed in the two preceding datasets. The achieved classification accuracy showed a consistent trend of superiority across the features, ranging from 99.45% to 99.85%. Particularly noteworthy was the top-tier accuracy attained by the proposed method by employing feature fusions $\boldsymbol{F}_{10}$, $\boldsymbol{F}_3$, and $\boldsymbol{F}_{11}$, with remarkable accuracies of 99.85%, 99.82%, and 99.77%, respectively. Interestingly, the feature fusions that produced the highest accuracy on Supermarket produce dataset is the same as Ubaya-IFDS3000 dataset.

This study also compared classification accuracy between the proposed method and optimized SVM based on RSO, AOA, TSA, HHO, BO for hyperparameter tuning. Table 3 presents a comparative analysis of the proposed method against other optimization algorithms in terms of accuracy across different datasets. In Ubaya-IFDS3000 dataset with feature fusion CS+SC, optimized SVM

Table 3. Comparison of the proposed method with the other optimization algorithms

Optimization algorithm	Accuracy (%)
Ubaya- IFDS3000 dataset with CS+SC	
RSO	98.32
AOA	98.91
TSA	99.13
HHO	98.91
BO	98.84
GWO (this study)	**99.21**
Ubaya- IFDS3000 dataset with CS+SC+CL+HT	
RSO	97.27
AOA	97.97
TSA	97.82
HHO	98.25
BO	96.90
GWO (this study)	**98.29**
Supermarket produce dataset with CS+SC+CL	
RSO	99.79
AOA	99/79
TSA	99.82
HHO	99.83
BO	99.79
GWO (this study)	**99.85**

based on GWO outperforms alternative algorithms with an accuracy of 99.21%, surpassing RSO, AOA, TSA, HHO, and BO, which scored 98.32%, 98.91%, 99.13%, 98.91%, and 98.84% respectively. Similarly, on the Ubaya-IFDS5000 dataset with feature fusion CS+SC+CL+HT, GWO achieves an accuracy of 98.29%, surpassing RSO, AOA, TSA, HHO and BO, which scored 97.27%, 97.97%, 97.82%, 98.25% and 96.90% respectively. The comparison extends to the Supermarket produce dataset with feature fusion CS+SC+CL, where GWO demonstrates the highest accuracy at 99.85%, surpassing RSO, AOA, TSA, HHO and BO, which achieved 99.79%, 99.79%, 99.82%, 99.83%, and 99.79% accuracy respectively. These results underscore the superior performance of the proposed GWO method across various datasets in fruit image classification.

The classification performance of the proposed method was also compared to other classification methods proposed in previous studies in classifying fruit images on Ubaya-IFDS3000 and Supermarket produce datasets, as shown in Table 4 and Table 5, respectively. Previously, two studies have utilized the Ubaya-IFDS3000 dataset. The first study employed an ensemble of k-nearest neighbors (k-NN) and Linear Discriminant Analysis (LDA) with features CS, SC, CL+EH [6]. The second study used an ensemble of optimized Extreme Learning Machines (ELMs) with features SC+HT, CS+SC+CL, CS+SC+HT [9]. As shown in Table 4, the proposed method with features CS+SC,

Table 4. Comparison of the proposed method with the previous studies on Ubaya-IFDS3000 dataset

Method	Accuracy (%)
Ensemble of *k*-NN and LDA [6]	97.80
Ensemble of optimized ELMs [9]	98.03
Enhanced SVM based on GWO with CS+SC (this study)	**99.21**

demonstrates superior performance. These results indicate that the proposed method outperforms the previous studies regarding classification accuracy on the Ubaya-IFDS3000 dataset.

For Supermarket Produce dataset, several methods have been proposed to classify fruit images in this dataset both for traditional machine learning and deep learning approaches. For traditional machine learning approach, there were SVM-fusion with input features global color descriptor (GCH), Unser descriptor, and color coherent vector (CCV) [10], automatic classifier fusion [11], SVM with an improved sum and difference histogram (ISADH) as input features [12], SVM with input features fusion of color and texture features [16], and SVM with input features census transform histogram (CENTRIST) and hue saturation histogram [8].

For deep learning approach, there were six layers of convolutional neural network (CNN) with data augmentation and pretrained visual geometry group-16 (VGG-16) model [24], attention-based MobileNetV2 [28], and optimized RNN with DenseNet169 as feature extraction [29]. As shown in Table 5, the proposed method outperforms the results of previous studies in classifying fruit images from Supermarket Produce dataset. Even though the VGG-16 [24] and optimized RNN [29] produced

Table 5. Comparison of the proposed method with the previous studies on Supermarket produce dataset

Method	Accuracy (%)
SVM-fusion with GCH+Unser+ CCV [10]	97.00
Automatic classifier fusion [11]	98.80
SVM with ISADH [12]	99.00
SVM with fusion of color and texture features [16]	93.84
SVM with CENTIRIST+ Hue Saturation Histogram [8]	97.23
AlexNet with data augmentation [26]	99.46
Six layers of CNN with data augmentation [24]	99.49
VGG-16 [24]	99.75
Attention-based MobileNetV2 [28]	95.75
DenseNet169+Optimized RNN [29]	99.84
Enhanced SVM based on GWO with CS+SC+CL (this study)	**99.85**

almost the same accuracy as the proposed method, these methods required more training data (85% and 70%, respectively) than the proposed method in this study (50%). Furthermore, optimized RNN [29] only used 75 samples per class in Supermarket produce dataset in the experiment.

4. Conclusion

This study proposes an enhanced support vector machine (SVM) based on grey wolf optimizer (GWO) to classify fruit from images. GWO, inspired by the social behavior of grey wolves, has been employed successfully for optimizing the hyperparameters of SVM and the threshold of low variance feature selection. This approach demonstrates its potential in improving SVM accuracy, using MPEG-7 visual descriptors fusion as input features, avoiding the need for preprocessing and segmentation steps. The experimental results show that the proposed method produced remarkable accuracies across three diverse datasets. The top-performing feature fusions, particularly CS+SC, CS+SC+CL+HT, and CS+SC+CL, consistently outshine others, yielding impressive average accuracies of 99.21%, 98.29%, and 99.85% on the Ubaya-IFDS3000, Ubaya-IFDS5000, and Supermarket produce datasets, respectively.

Comparative analyses against alternative optimization algorithms and previous studies highlight the superiority of the proposed GWO-based method. Across various datasets, the optimized SVM using GWO consistently outperforms RSO, AOA, TSA, HHO, and BO, with accuracy differences ranging from 0.02% to 1.39%. Moreover, when compared to previous studies, the proposed method demonstrates superior performance on both Ubaya-IFDS3000 and Supermarket produce datasets, showcasing its efficacy in fruit image classification. In addition to the GWO employed in this study for hyperparameter optimization, future research can explore alternative metaheuristic optimization techniques further to enhance the performance of fruit image classification models in traditional machine learning and deep learning models.

Conflicts of Interest

The authors declare no conflict of interest.

Acknowledgments

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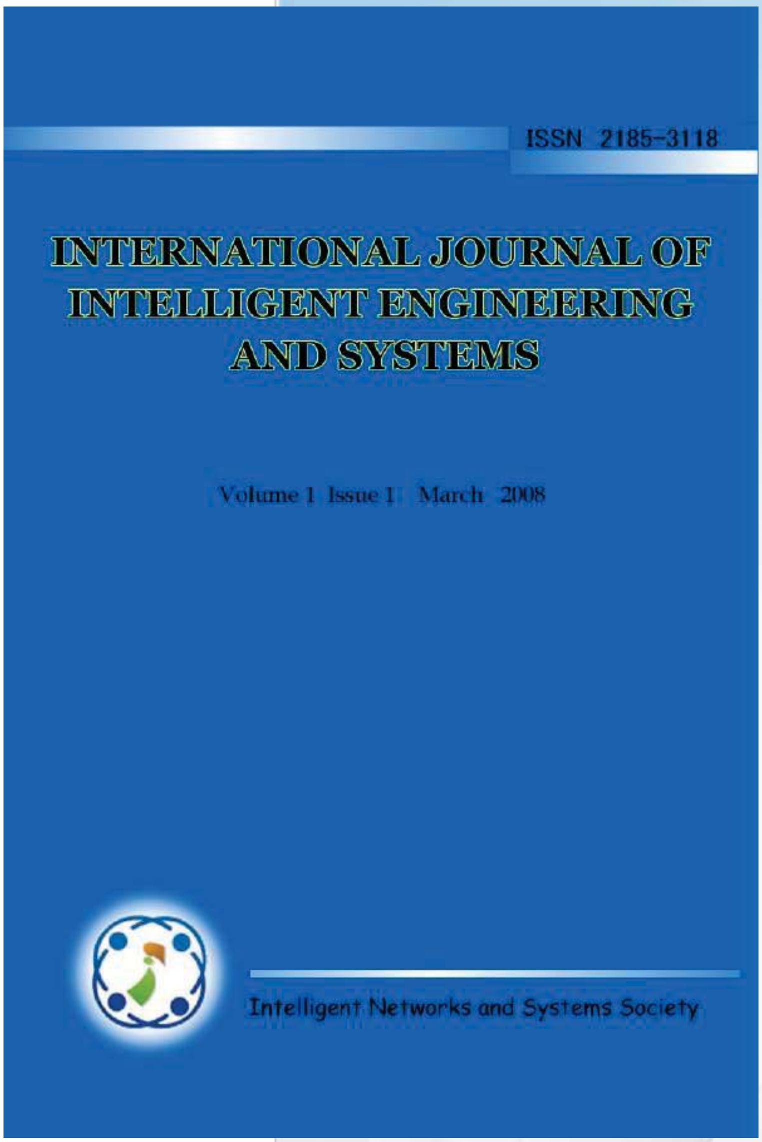

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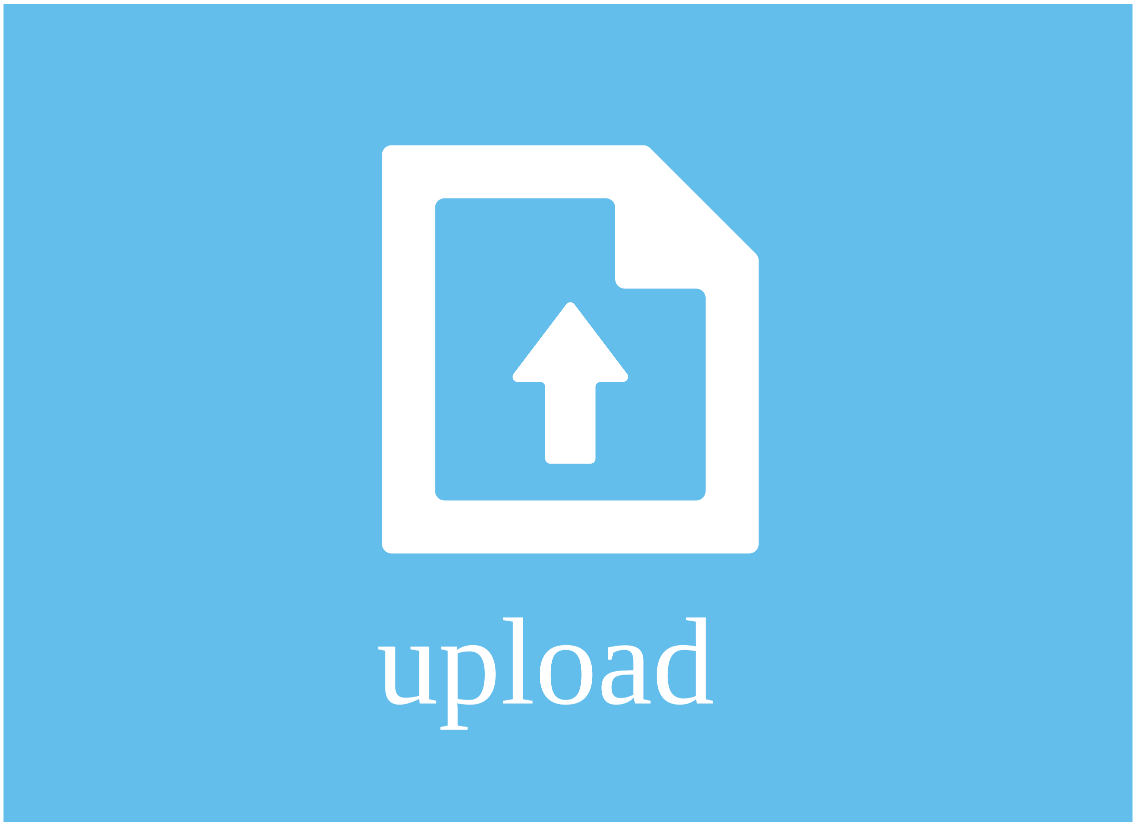

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Dear Editor-in-Chief of The Intelligent Network and Systems Society

Thank you for reviewing our manuscript with paper ID 202[illegible]88 entitled "Enhanced Support Vector Machine Based on Grey Wolf Optimizer for Fruits Image Classification Using [illegible] Color and Texture Features Fusion". We also greatly appreciate the reviewers for their complimentary comments and suggestions. Those comments are very valuable and beneficial for revising and improving the quality of our paper, but are also essentially significant to our future research. We have carefully studied the comments and made the revision, which we hope will meet with your approval. All revisions are written in red font and highlighted in yellow.

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Best regards,

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Thanks □or yo□r □nder standing and cooperation□

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INASS

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Thank yo□ □or yo□r inter est and s□ppor t to I□I□S□
I am here□y to confirm the deli□ery o□ yo□r paper□
It has □een sent □or re□iewing□
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□eg□lar □□□lication□ The noti fication will □e □eed□ack within one month□
□ppr eciate yo□r patiently wait □

If you have any questions, please contact us with your paper ID.

Best regards,
IJIES Editors, ijies@inass.org
[illegible]

Comment Date 202[illegible]

Joko Siswantoro

Dear Editor-in-Chief,
International Journal of Intelligent Engineering and Systems

I am writing to submit my article entitled "Enhanced Support Vector Machine Based on Grey Wolf Optimizer for Fruits Image Classification Using [illegible] Color and Texture Features Fusion" for consideration and possible publication in the International Journal of Intelligent Engineering and Systems.

This manuscript represents original and unpublished work, showcasing an innovative approach to fruit image classification by enhancing Support Vector Machine (SVM) performance through the integration of Grey Wolf Optimizer (GWO) and the fusion of [illegible] color and texture features. The research contributes to the field by improving the accuracy and efficiency of fruit image classification systems, which has implications for various applications, including agricultural automation and food quality assessment.

I believe that the research presented in this manuscript aligns well with the scope and objectives of the International Journal of Intelligent Engineering and Systems. The novelty and significance of the proposed methodology make it a valuable contribution to the field of intelligent engineering and systems.

I kindly request that you consider this submission for peer review. I believe that the findings presented in this manuscript will be of interest to the readership of your esteemed journal, and its publication would contribute significantly to the existing body of knowledge in the field.

Thank you for considering my submission. I look forward to receiving feedback from the reviewers and hope for the opportunity to contribute to the International Journal of Intelligent Engineering and Systems.

Best regards,

Dr. Joko Siswantoro
University of Surabaya
Surabaya, East Java, Indonesia
Email: joko_siswantoro@staff.ubaya.ac.id

Comment [illegible]ate 202[illegible] [illegible]2[illegible]

International Journal of Intelligent Engineering and Systems

COUNTRY

Japan

Universities and research institutions in Japan

Media Ranking in Japan

SUBJECT AREA AND CATEGORY

Computer Science
└ Computer Science (miscellaneous)

Engineering
└ Engineering (miscellaneous)

PUBLISHER

Intelligent Networks and Systems Society

H-INDEX

30

PUBLICATION TYPE

Journals

ISSN

2185310X, 21853118

COVERAGE

2008-2023

INFORMATION

Homepage

How to publish in this journal

ijies@inass.org

SCOPE

International Journal of Intelligent Engineering and Systems is an OPEN ACCESS international journal which gains a foothold in Asia and opens to the world. It aims to promote the integration of intelligent engineering and systems. The focus is to publish papers on state-of-the-art intelligent computing, network engineering, electrical/electronics engineering, and industrial engineering and systems, with emphasis on novel technologies, theoretical work and engineering applications. The audience includes researchers, managers and operators for intelligent engineering and systems as well as designers and developers.

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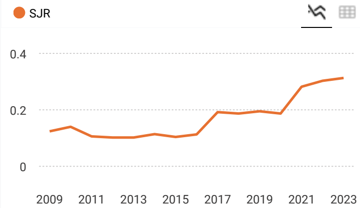

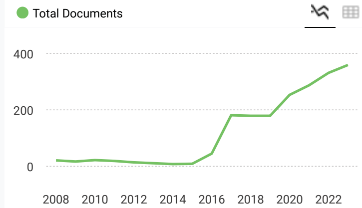

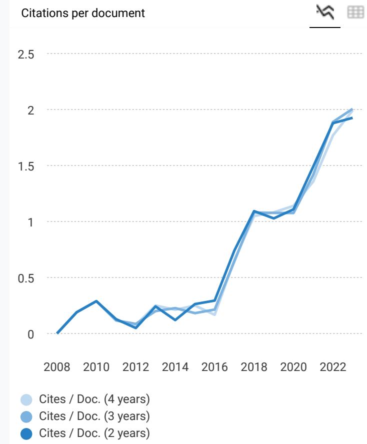

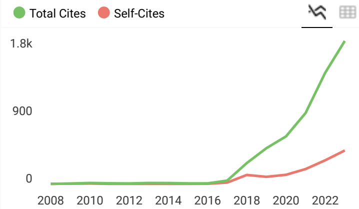

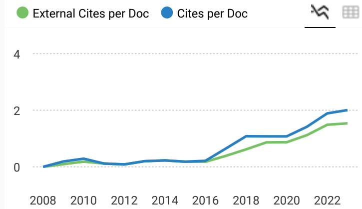

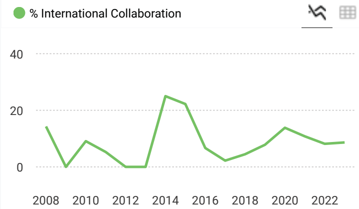

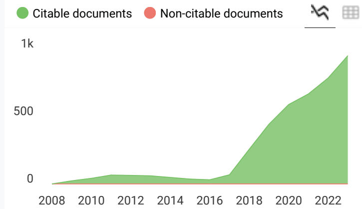

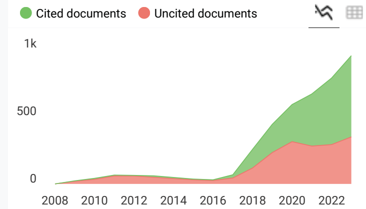

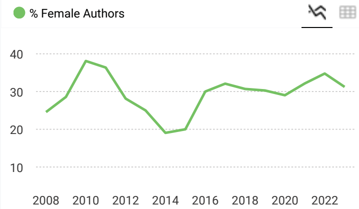

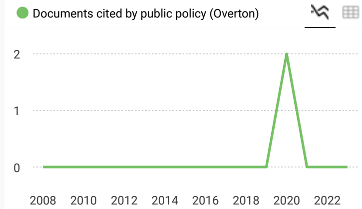

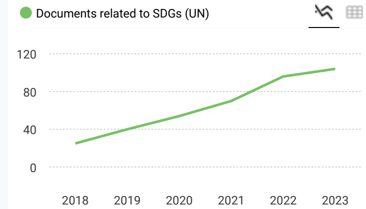

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SCImago Graphica

Explore, visually communicate and make sense of data with our **new data visualization tool**.

Metrics based on Scopus® data as of March 2024

N

Nameer 4 weeks ago

Dear Scimago Team,

I would like to seek clarification regarding the quartile rankings for the year 2023.

I have observed that the CiteScore on Scopus for this journal indicates that both subject areas for the journal are classified as Q2. However, on your platform, the ranking reflects Q3 for Computer Science and Q2 for Engineering.

reply

SCImago Team

Melanie Ortiz 3 weeks ago

Dear Nameer,
Thank you for contacting us.
As you probably already know, our data come from Scopus, they annually send us an update of the data. This update is sent to us around April / May every year.
The calculation of the indicators is performed with the copy of the Scopus database provided to us annually. Regarding your inquiry about the Quartile distribution process at SCImago, the journals are ranked and distributed in 4 equal groups based on their SJR value, unlike Scopus, who ranks the publications by percentiles based on the journal's CiteScore.
The Quartile methodology, like others that are used to group results such as percentiles, can be applied to any indicator. Currently, Scopus offers information on the journals ranking and the percentile they occupy according to the CiteScore indicator (https://service.elsevier.com/app/answers/detail/a_id/14880/supporthub/scopus/), which is perceived as an impact indicator, but that is different from the SJR, as the latter is also a normalized impact indicator (https://www.scimagojr.com/files/SJR2.pdf).
Both Scopus and SCImago Journal and Country Rank offer information on the SJR indicator for every journal, although the position of each of the publications and the quartile in which it is located according to the SJR can be consulted at https://www.scimagojr.com.
According to the above, the difference in the information consulted on the Scopus journal's profile and in Scimagojr.com lies in the fact that they represent the position of the journal based on two different indicators, which are not directly comparable because they measure two different dimensions: Impact (CiteScore) and Normalized Impact (SJR).
Additionally, it is important to keep in mind that, although the quartiles in SJR tend to be distributed in 4 groups of equal size and that the journals appear sorted by the highest SJR to the lowest SJR, it is not always possible due to ties in SJR values and, therefore, journals with the same SJR must be distributed within the same quartile, which may lead to differences in the number of journals within that quartile.
Best Regards,
SCImago Team

A

Ari Azhari 2 months ago

Hello Melanie and all,

This journal is very competitive with a high rate of accepting. Such as: 2023 Acceptance Rate at 14.1%, 2022 Acceptance Rate at 15.2%, 2021 Acceptance Rate: 13.7% (see at: https://inass.org/publications/)

As a lot of my graduate students mentioned to me, this journal is very competitive. They sent their papers to this journal because of the very quick response of the first decision (about two weeks). Even so, they know that only a few papers succeeded in being accepted. Whereas many of my student papers make a good contribution or have an innovation with strong novelty in their scope of topics. Such as: modifying an existing method, developing a hybrid approach to solve complex problems, etc.

Best regards

reply

SCImago Team

Melanie Ortiz 2 months ago

Dear Ari, thanks for your participation! Best Regards, SCImago Team

D

Dr. Rasool 3 months ago

I have experience with this journal, having submitted my work to them twice. Each time, the review process took about two weeks, after which the reviewers provided a few irrelevant comments that did not pertain to my paper and were not from specialists in the field. It seems possible that the editor might also be acting as a reviewer. Additionally, the editor's responses have been quite rude. I feel that this journal wastes authors' time and is disappointing. I do not recommend it and regret that it is indexed by Scopus.

reply

R

Rashmi 2 weeks ago

Dear Sir,
i have filled the form for submission ,waiting from last 16 days to receive mail for submission link.not yet received. I have contacted their email editorial too.

its my phd work. I am worried .

can you help me on this

Melanie Ortiz 2 months ago SCImago Team

Dear Dr. Rasool, thanks for your participation! Best Regards, SCImago Team

W

WK 4 months ago

Dear Sir,

can i know the impact factor of International Journal of Intelligent Engineering and Systems journal ?

reply

Melanie Ortiz 4 months ago SCImago Team

Dear WK, thank you very much for your comment. SCImago Journal and Country Rank uses Scopus data, our impact indicator is the SJR (Check it above). We suggest you consult the Journal Citation Report for other indicators (like Impact Factor) with a Web of Science data source. Best Regards, SCImago Team

"

"Ravikiran Reddappa Reddy" 5 months ago

When can my paper titled "UNNIGSA: A Unified Neural Network Approach for Enhanced Stutter

Detection and Gait Recognition Analysis" will be publishing?

reply

RAVIKIRAN R 5 months ago

What is the status of my paper titled "UNNIGSA: A Unified Neural Network Approach for Enhanced Stutter Detection and Gait Recognition Analysis" and paper id is 20240327. Please acknowledge me when will be the acceptance and publication?

Melanie Ortiz 5 months ago SCImago Team

Dear Ravikiran,
Thank you for contacting us.
We are sorry to tell you that SCImago Journal & Country Rank is not a journal. SJR is a portal with scientometric indicators of journals indexed in Elsevier/Scopus.
We suggest you contact the journal's editorial staff , so they could inform you more deeply.
Best Regards, SCImago Team

Y

Yuan 5 months ago

Dear SCImago,
i already register an account for paper submission on INASS, but it's already a week i don't receive any email that contain password to login on "Mypage" in INASS website. How do I resolve that?
Thank you

Melanie Ortiz 5 months ago SCImago Team

Dear Yuan,
Thank you for contacting us.
We are sorry to tell you that SCImago Journal & Country Rank is not a journal. SJR is a portal with scientometric indicators of journals indexed in Elsevier/Scopus.
We suggest you contact the journal's editorial staff , so they could inform you more deeply.
Best Regards, SCImago Team

SCImago Team

Melanie Ortiz 5 months ago

Dear Ravikiran,
Thank you for contacting us.
We suggest you visit the journal's homepage or contact the journal's editorial staff , so they could inform you more deeply.
Best Regards, SCImago Team

F

Fahd Ahmad 8 months ago

I had bad experience with this journal, although my paper was accepted, when the payment supposed to be USD300, i got invoice for USD500, but i got direct and unpolite response, (this journal does not suit your paper, withdraw the paper and submit it elsewhere', i believe the editor of this journal is not ok. totally rude and no respect to the time and effort we spent in writing.

reply

G

Gill 6 months ago

Can you please share the time they took for reviewing your work?

SCImago Team

Melanie Ortiz 8 months ago

Dear Fahd, thanks for your participation! Best Regards, SCImago Team

S

SHASHIKALA S 11 months ago

Dear Editor ,

IJIES scopus coverage is till 2023 only .

And i checked in SCOPUS List also its till Dec 2023.

As i am publishing this for my Phd work

Is this journal will continue in scopus or as mentioned in the SCOPUS r they discontinue after 2023.
Please guide to proceed further for publication in this journal.

reply

SCImago Team

Melanie Ortiz 11 months ago

Dear Shashikala,
Thank you very much for your comment.
We suggest you consult the Scopus database directly to see the current index status as SJR is a static image of Scopus, which is changing every day.
The Scopus' update list can also be consulted here:
https://www.elsevier.com/solutions/scopus/how-scopus-works/content
For further information, please contact Scopus support team here: https://service.elsevier.com/app/answers/detail/a_id/14883/kw/scimago/supporthub/scopus/
Best Regards, SCImago Team

T

TRƯƠNG CÔNG TOẠI 1 year ago

Dear SCImagoTeam,
Can you give me some information about the IF of this journal?
Thanks.

reply

Y

Yogesh Kirange 1 year ago

On Scopus.com , it shows coverage from 2008 to present but here on scimago it shows coverage from 2008 to 2022. Which one is correct?

SCImago Team

Melanie Ortiz 1 year ago

Dear Yogesh,
Thank you for contacting us.
SCImago is updated only once a year (latest update May 2023), after receiving the Scopus'annual update.
For this reason, we always recommend to consult the Scopus database directly to see the current index status of a journal.
In addition, you can check the updated Scopus journals list released regularly by Elsevier by checking the link below:
https://www.elsevier.com/solutions/scopus/how-scopus-works/content
Best Regards, SCImago Team

SCImago Team

Melanie Ortiz 1 year ago

Dear Truong, thank you very much for your comment. SCImago Journal and Country Rank uses Scopus data, our impact indicator is the SJR (Check it on our website). We suggest you consult the Journal Citation Report for other indicators (like Impact Factor) with a Web of Science data source. Best Regards, SCImago Team

J

Jack 1 year ago

Dear SCImagoTeam,

Just want to ask, is it a different way to compute the quartile between ScimagoJR.com and Scopus.com? For example, for this journal, the International Journal of Intelligent Engineering and Systems is listed as the second quartile in Scopus.com. But with the same SJR, it has a Q3 badge on Scimagojr.com.
Thank you and regards

reply

SCImago Team

Melanie Ortiz 1 year ago

Dear Jack, Thank you for contacting us.
As you probably already know, our data come from Scopus, they annually send us an update of the data. This update is sent to us around April / May every year.
The calculation of the indicators is performed with the copy of the Scopus database provided to us annually. However, the methodology used concerning the distribution of Quartiles by Scopus is different from the one used by SCImago.
For every journal, the annual value of the SJR is integrated into the distribution of SJR values of all the subject categories to which the journal belongs. There are more than 300 subject categories. The position of each journal is different in any category and depends on the performance of the category, in general, and the journal, in particular. The distribution by Quartiles cannot be considered over the journals' total amount within a Category. In the case of SCImago, the distribution has to be considered with the formula Highest-SJR minus Lowest-SJR divided into four.
Best Regards,
SCImago Team

S

Satish 2 years ago

is this journal still (January 2023) Scopus indexed?

reply

SCImago Team

Melanie Ortiz 2 years ago

Dear Satish,
Thank you very much for your comment.
All the metadata have been provided by Scopus /Elsevier in their last update sent to SCImago, including the Coverage's period data. The SJR for 2021 was released on 11 May 2022. We suggest you consult the Scopus database directly to see the current index status as SJR is a static image of Scopus, which is changing every day.
The Scopus' update list can also be consulted here:
https://www.elsevier.com/solutions/scopus/how-scopus-works/content
Best Regards, SCImago Team

A

Aws Alkhazraji 2 years ago

Dear Editor,
in date 2022 octuber
What is the current journal Rank as it appears in Scopus 53rd percentile

Thank you

reply

SCImago Team

Melanie Ortiz 2 years ago

Dear Aws,
Thank you for contacting us. Our data come from Scopus, they annually send us an update of the data. This update is sent to us around April / May every year. The SJR for 2021 was released on 11 May 2022. Therefore, the indicators for 2022 will be available in May/June 2023 and before that date we can´t know what will happen with this journal.
Best Regards, SCImago Team

S

Shdotcom 2 years ago

Dear Editor,

What is the percentile range of Q2, is it 50th-74th or 51st-75th?

Thank you

reply

SCImago Team

Melanie Ortiz 2 years ago

Dear Shdotcom,
Thank you for contacting us.
The distribution by Quartiles cannot be considered over the journals' total amount within a Category. In the case of SCImago, the distribution has to be considered with the formula Highest-SJR minus Lowest-SJR divided into four.
Best Regards, SCImago Team

Y

Yashaswini DK 3 years ago

From when journal IJIES is dropped fromQ2to Q3

reply

SCImago Team

Melanie Ortiz 3 years ago

Dear Yashaswini , thank you very much for your comment. The SJR for 2020 has been released on 17 May 2021. Each year, Scopus provides us an update of their database and, according to that information, the scientometric indicators are calculated. The annual data's update can change the journal's quartile.
Best Regards, SCImago Team

A

Ali 3 years ago

Dear SCImago team,
I need to reuse some parts of the published articles by your journal in a book that I am intending to write. I need a permission of the copyright holder to do so, all parts will be cited and referred to in the book. Could you please advise or help to resolve such issue?
Kindest regards
Ali

reply

SCImago Team

Melanie Ortiz 3 years ago

Dear Ali,
Thank you for contacting us.
We are sorry to tell you that SCImago Journal & Country Rank is not a journal. SJR is a portal with scientometric indicators of journals indexed in Elsevier/Scopus.
We suggest you contact the journal's editorial staff , so they could inform you more deeply.
Best Regards, SCImago Team

M

Mohamed 3 years ago

Please I want to know the date that the rank of this journal was changed from Q2 to Q3

reply

SCImago Team

Melanie Ortiz 3 years ago

Dear Mohamed,
Thank you for contacting us. Our data come from Scopus, they annually send us an update of the data. This update is sent to us around April / May every year. The SJR for 2020 was released on 17 May 2021.
Best Regards, SCImago Team

I

IJIES Editor 3 years ago

Dear Melanie Ortiz

The website of the International Journal of Intelligent Engineering and Systems (IJIES) has been updated as follows:

Homepage:
https://inass.org/

How to publish in this journal:
https://inass.org/publications/pub-submissionguidelines/

Thank you
---

reply

SCImago Team

Melanie Ortiz 3 years ago

Dear Sir/Madam, thanks for your participation! Best Regards, SCImago Team

D

donya 3 years ago

Dear Editor ..
In 2021 . 7
in which Q , International journal of intelligent Engineering and system ??

Best Regards

reply

SCImago Team

Melanie Ortiz 3 years ago

Dear Donya, thank you very much for your request. You can consult that information just above. Best Regards, SCImago Team

U

umasankar 3 years ago

whether the paper may be indexed by the scopus from this journal (IJIES)
what is the procedure for indexing the paper in each and every journal.
why because some papers only indexed in each and every journal what is the reason can you explain please

reply

SCImago Team

Melanie Ortiz 3 years ago

Dear Umasankar,
thank you very much for your comment, unfortunately we cannot help you with your request. We suggest you contact Scopus support: https://service.elsevier.com/app/answers/detail/a_id/14883/kw/scimago/supporthub/scopus/
Best Regards, SCImago Team

A

ahmed 3 years ago

The journal was classified as Q2 now it is Q3, Why is this drop ?
what are the metrics for this classifcation?
what is the frequany of updating the data and ranking of the journals in scimagojr website ?
Thanks

reply

SCImago Team

Melanie Ortiz 3 years ago

Dear Ahmed, thank you very much for your comment. The SJR for 2020 has been released on 17 May 2021. Each year, Scopus provides us an update of their database and, according to that information, the scientometric indicators are calculated. The annual data's update can change the journal's quartile.
The SJR indicator is a very sophisticated indicator. To know more about it, click here: https://www.scimagojr.com/files/SJR2.pdf
Best Regards, SCImago Team

N

Neetu Manocha 4 years ago

Respected Sir
I m a Ph.D. Research scholar. I want to publish my research paper in your journal. Please tell me that how much time will take to publish my research paper. Because my presubmission is dependent on only acceptance of my research paper.

reply

SCImago Team

Melanie Ortiz 4 years ago

Dear Neetu,
thank you for contacting us.
We are sorry to tell you that SCImago Journal & Country Rank is not a journal. SJR is a portal with scientometric indicators of journals indexed in Elsevier/Scopus.
Unfortunately, we cannot help you with your request, we suggest you visit the journal's homepage (See submission/author guidelines) or contact the journal's editorial staff , so they could inform you more deeply.
Best Regards, SCImago Team

K

kanaan A. Jalal 4 years ago

Dear Editor,
I would like to ask about the accepted permissiable percentage of plagiarism in your respected journal.
best regards
Kanaan

reply

SCImago Team

Melanie Ortiz 4 years ago

Dear Kanaan,
thank you for contacting us.
We are sorry to tell you that SCImago Journal & Country Rank is not a journal. SJR is a portal with scientometric indicators of journals indexed in Elsevier/Scopus.
Unfortunately, we cannot help you with your request, we suggest you visit the journal's homepage or contact the journal's editorial staff , so they could inform you more deeply.
Best Regards, SCImago Team

M

Maral A. Mustafa 5 years ago

Dear Editor

I hope this message finds you well.
I want to publish my research article in your respectable journal but my problem is the payment way,in my country there is no pay pal (credit card).please help me to pay the publication fee by western union way

Best regards,

Maral A. Mustafe
Iraq

reply

Melanie Ortiz 5 years ago SCImago Team

Dear Maral,
thank you for contacting us.
We are sorry to tell you that SCImago Journal & Country Rank is not a journal. SJR is a portal with scientometric indicators of journals indexed in Elsevier/Scopus.
Unfortunately, we cannot help you with your request, we suggest you to contact the journal's editorial staff , so they could inform you more deeply.
Best Regards, SCImago Team

D **Dr rajshekar** 5 years ago

good morning
can i know the impact factor of this journal ?
thank you

reply

Melanie Ortiz 5 years ago SCImago Team

Dear user, SCImago Journal and Country Rank uses Scopus data, our impact indicator is the SJR. Check our web to locate the journal. We suggest you to consult the Journal Citation Report for other indicators (like Impact Factor) with a Web of Science data source. Best Regards, SCImago Team

D **Dr. A. Ragavendiran** 5 years ago

Dear Editor
I want to publish my research article in your respectable journal but there is no author instruction and submission page.

reply

D **Doaa Abdullah** 6 years ago

Dear Editor,

I hope this message finds you well.
I want to publish my research article in your respectable journal but I have a problem of lack of time for my master thesis.

Could you please tell me how long does it usually take to be reviewed? And is there is any way to squeeze the required reviewing time?

Best regards,
Doaa

reply

Elena Corera 6 years ago SCImago Team

Dear Doaa Abdullah,

thank you very much for your comment, unfortunately we cannot help you with your request. We suggest you check author's instructions in journal website. You can find that information in SJR website https://www.scimagojr.com

Best Regards,
SCImago Team

M

Mostafa 6 years ago

Dear Editor
I have a problem with lack of time.
because I need to accept the paper for doctoral thesis defense and my time is limited to one and half month.
I have a shortage of time to accept the paper.
How long does your jury review an article?
How long will your journal accept an article?
Is it possible to review my article as soon as possible?
thank you.

reply

C

chan.chung.lee@gmail.com 6 years ago

I can help you contact me for publication

Leave a comment

Name

Email
(will not be published)

Submit

The users of Scimago Journal & Country Rank have the possibility to dialogue through comments linked to a specific journal. The purpose is to have a forum in which general doubts about the processes of publication in the journal, experiences and other issues derived from the publication of papers are resolved. For topics on particular articles, maintain the dialogue through the usual channels with your editor.

Source details

International Journal of Intelligent Engineering and Systems

Years currently covered by Scopus: from 2008 to 2024

Publisher: Intelligent Networks and Systems Society

ISSN: 2185-310X E-ISSN: 2185-3118

Subject area: Engineering: General Engineering | Computer Science: General Computer Science

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