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Marigold Blooming Maturity Levels Classification Using Machine Learning Algorithms

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Abstract

Image processing is swiftly progressive in the area of computer science and engineering. Image classification is a fascinating task in image processing. In this study, we have classified the marigold blooming maturity levels like a marigold bud, partial blooming marigold, and fully blooming marigold. To classify the marigold blooming maturity levels are a tough and time-consuming task for human beings. Hence, an automatic marigold maturity levels classification tool is very adjuvant even for experience humans to classify the huge number of marigolds. For the sake of that, we have deliberated a novel system to classify automatically marigold blooming maturity levels image data by using machine learning algorithms. There are three types of machine learning models namely Artificial Neural Network(ANN), Convolutional Neural Network(CNN), and Support Vector Machine(SVM) that are used to automatically classify marigold maturity levels. Hence, we have preprocessed the image at first. Then we extract the various features from the marigold images. After that, these features have fed into Machine Learning(ML) models and classify these images into the category. From the experiment, we observed that the Convolutional Neural Network (CNN) model provides a high accuracy compared to other Artificial Neural Network(ANN) and Support Vector Machine(SVM) algorithms. The Convolutional Neural Network(CNN) models performed the best among all two classifiers with an overall accuracy of 93.9%. Our proposed system is efficiently classifying marigold maturity levels.

Keywords: Machine Learning(ML); Deep learning(DL); Artificial Neural Network(ANN); Convolutional Neural Network(CNN); Support Vector Machine(SVM); Confusion Matrix(CM).

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1. Introduction

There are many kinds of flowers in the universe. The attraction of people towards flowers in terms of beauty has been going on since ancient times. Flowers are a symbol of beauty, holiness, reverence, and love. There are different types of flowers in the world. Over the last ten to twenty years there have been various studies on flowers image in the world among the studies includes flowers image classification, flower species classification, color detection, and flower maturity detection, etc. There is currently a lot of research being done on flower images using machine learning algorithms. In[1] recent years, image processing plays a vital role in the field of machine learning. Image processing (IP) means extracting useful information from the image. The flower image classification works much like general image classification like a cat, dog, cow, etc [2]. Presently, flower blooming classification is a vital topic to identify specific flowers type or flower maturity and predicts their levels.The Machine Learning (ML) algorithms are used to apply the image classification and Machine Learning (ML) models provide high accuracy at the feasible computation speed. Deep learning algorithm special convolutional neural network has been widely used in image processing areas including flower types or flower maturity classification in recent times. For that, much research is being conducted on image processing by machine learning and deep learning algorithms. The categorical flower image classification is a grand job in the concern of image processing. The flower blooming maturity level forecast is also an important task in image processing using machine learning techniques because it is critical to identify the flower blooming maturity level manually and time-consuming also for humans being. In this study, a novel system is represented which is the association of three classification models, Artificial Neural Network(ANN), Convolutional Neural Network(CNN), and Support Vector Machine(SVM), with eleven distinct sets of features [3]. The features extracted are average red color, average green color, average blue color, average hue color, average saturation color, average values color, horizontal and vertical contrast, horizontal and vertical correlation, horizontal and vertical energy, horizontal and vertical homogeneity, gray-level co-occurrence matrix (GLCM), and extract automatic various features for Convolutional Neural Network(CNN) algorithm and their convention. These features have fed to train the machine learning(ML) models (ANN, SVM, and CNN) for classifying the marigold blooming maturity levels. Our marigold blooming image dataset contained 3070 marigold images that are categorized into three classes of flowers namely marigold bud, partially blooming marigold, fully blooming marigold. From the experimental result, we have observed that the Convolutional Neural Network(CNN) algorithm classifies the marigold blooming maturity level accurately from other Machine Learning(ML) algorithms namely Artificial Neural Network(ANN), and Support Vector Machine(SVM) algorithms. From our viewing, the Convolutional Neural Network(CNN) model depicts the highest classification accuracy is (93.9%) and other Machine Learning Artificial Neural Network(ANN), and Support Vector Machine(SVM) models that achieve the classification accuracies are (72.2%) and (86.4%) respectively. The rest of this paper is as follows. Section 2 describes the literature review. Section 3 represents the dataset and methodology. Section 4 depicts the results and evaluates the performance of the classifiers and Section 5 displays the conclusion.

2. Literature Review

M. E. Nilsback and his colleagues [4] introduced the 103 class dataset used for their classification task. They were used Support Vector Machine(SVM) machine learning models to classify the different flower images.

Here, the authors have computed four distinct features for the flowers, each describing different aspects, namely the local texture, the shape of the boundary, the overall spatial distribution of petals, and the color. They were achieved the highest and the lowest accuracy 72.8% and 55.1% for all features and single features respectively. The limitation of their work is that accuracy would have been better if they used deep learning. The authors in [5] were used Artificial Neural Network(ANN) and Logistic Regression(LR) models to classify the flower images. Here, the authors have used about eighteen hundred images and they have classified thirty types of flowers. For their flower classification, authors also extracted various features from the training images namely color, texture, correlation, HSV, etc. From their experiment, the Artificial Neural Network(ANN) model has provided a high accuracy than Logistic Regression(LR) model. But still, there is a research gap because they were used 1800 flower images with 30 classes for that machine learning algorithms may provide error result. The authors in [6] tried to flower blooming recognition by using eigenvalues of shape features. Here, they were derived various features such as RGB color, shape for recognizing the blooming images. They were taken images of only five types of 46 flowers and the recognition rate is achieved by 80.43%. The authors have used a very small image dataset for that their proposed method may provide error results. This would be considered as a drawback of their study. Another flower classification work was described in [7]. They were classified the flower images to the use the Support Vector Machine(SVM) and Random Forest (RF) machine learning algorithms. During their study, a dataset consists of 215 flower samples with eight categories. Here, they were used two functions namely scale-invariant feature transform (SIFT) and segmentation-based fractal texture analysis (SFTA) which are used to extract flower features. From the experiment, they have observed the Support Vector Machine (SVM) model provides the highest accuracy than the RF model when they using SIFT feature function. On the other hand, Random Forests (RF) algorithm provides better accuracy with SFTA. For the classification, they were only 250 images with eight categories which would be considered as the limitation of their work because the machine learning algorithm may provide a biased result. The authors in[8] were classified flowe images using the Convolutional Neural Network(CNN) model. Here, they have used a large images dataset in 79 categories. In this study, the authors have achieved a classification accuracy of 76.54% by using their novel framework.S. Lu, Z. Lu and his colleagues [9] studied the application of machine learning in flower classification. Here, they considered only three classes of flower images and four machine learning algorithms namely Support Vector Machine(SVM), K-Nearest Neighbors(KNN); Kernel-Based Extreme Learning Machine(KBELM), Decision Tree(DT). Here, they have extracted color features and wavelet entropies from the petal images. The K-Nearest Neighbors(KNN) algorithm was provided the best accuracy than the other three classifiers and overall accuracy was achieved 99%. The research is limited to three classes and still, there is a drawback to display the flower image classification. P. Dhar and his colleagues [10] were tried to flower classification by using a machine learning Support Vector Machine(SVM) algorithm. Here, the authors were extracted Local Binary Patterns (LBP) and Speeded Up Robust Feature (SURF) features from the flower image for classifying the flower category level. They were fed these features to train the Support Vector Machine(SVM) classifier to classify the flower accurately and the Support Vector Machine(SVM) classifier achieves an accuracy of 87.2%. Here, they have used only one machine learning algorithm that is the gap of this classification task, and if they would have used the Convolutional Neural Network(CNN) model to get better results.

3. Methodology and Dataset

3.1 Dataset Description

The proposed system is demonstrated here using an algorithm and a block diagram. The block diagram is illustrated in the figure. (3.1). Here, We have provided several strategies for marigold blooming maturity level classification namely image pre-processing, segmentation, feature extraction, and classification. Finally, we have applied the machine learning algorithm with a view to classifying the marigold blooming maturity levels. When the training process is completed, the accuracy of the model is calculated using the test image and confusion matrix.

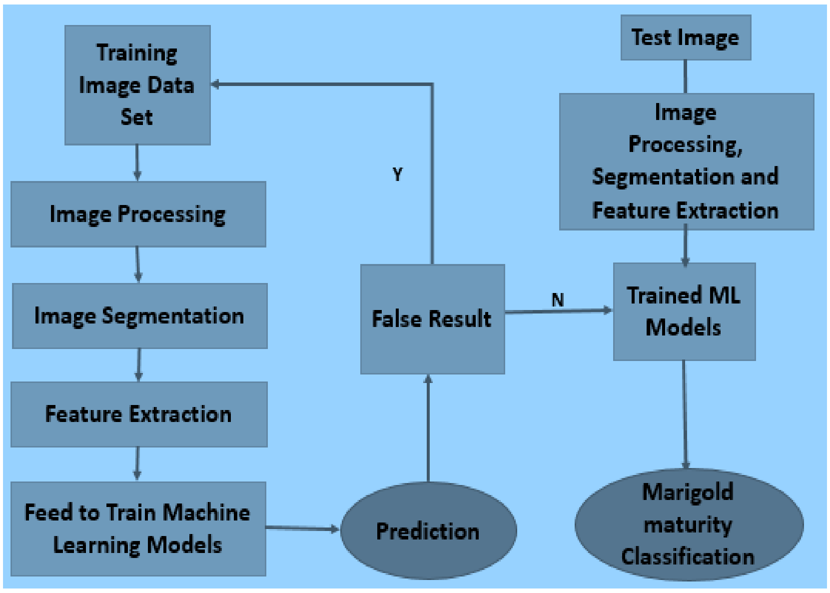

Figure 3.1: Proposed System Block Diagram

The algorithm of the proposed method is shown in Algorithm 1. This algorithm shows the steps of the proposed model.

Algorithm 1: Marigold Blooming Maturatiy Classification

Algorithm 1: Marigold Blooming Maturatiy Classification	
1	Read training images from the dataset
2	Pre-process images(resize, segmentation)
3	Extract the features(RGB,HSV).
4	Train the models (ANN, CNN, and SVM) to classify blooming maturity
5	Read test image
6	Apply the trained model to classify the blooming maturity of the test image.
7	Calculate classification_fault

8	If (false_Result > threshold)
	Go to step 1.
	Else
	good accuracy.

In this study, we have collected many marigold blooming images from the flower gardens of the Tangail

Polytechnic Institute at Tangail in Bangladesh.

Figure 3.2: Three levels (Marigold Bud, Partial Blooming Marigold and, Fully Blooming Marig Id) Images

These marigold images having three maturity levels were taken from Tangail Polytechnic flower gardens at Tangail district in Bangladesh. The marigold images are then grouped into three classes based on three levels of maturity shown in the figure. (3.2).

Table 3.1: Description of Image Dataset

Class Name	Marigold Blooming Maturity Label	No. of image
ClassA	Marigold Bud	1010
ClassB	Partial Blooming Marigold	1010
ClassC	Fully Blooming Marigold	1060
Total		3,070

Every class has contained more than one thousand images. The of each class is displayed in (Table3.1). The maturity of the marigold images is categorized as a marigold bud, partial blooming marigold, and fully blooming marigold. These marigold images are partitioned randomly into training (70%) and testing (30%) images respectively. We have captured all types of marigold images by android phone from the flower gardens of Tangail Polytechnic Institute at Tangail district in Bangladesh are depicted in the figure. (3.3).

Figure 3.3: Image acquisition sources.

3.1.1 Image Pre-processing

Image pre-processing is the most common term in digital image processing. Because capturing images may contain various noise and resolutions. For the sake of that, image pre-processing is needed and shunned noise and that's is depicted in the Table(3.2). Here, we have used Matlab resize() function to resize images to 320*180 pixels, image filter() function for smoothing. We have also applied the function rgb2gray() for eliminating the HSV information of the images.

Table 3.2: Image Preprocessing Function and description

ML Model	Description	Matlab Functions
ANN, SVM	Resize to 320 x 180 pixels	*resize()*
	Filtering for smoothing, sharpening, and edge enhancement	*filter()*
	The rgb2gray function for eliminating the hue and saturation information of the images.	*rgb2gray()*
	Graycomatrix function for texture analysis of the images.	*graycomatrix()*
CNN	Automatic resize and convert any grayscale images to RGB automatic and resizing to 224x224 RGB image. The CNN model resizes the training and testing images before the input to the network.	*augmentedImageDatastore()*

3.1.2 Image Segmentation

It is the second step of the marigold maturity image classification. Removing the unwanted background from the image is the second step in image classification. Because the original image contains various parts such as leaves, plants, grass, shapes, and shadow. We want to extract correct features so it is needed to separate the marigold image from its background.

Figure 3.4: Image Background Removal

There are many image segmentation methods to remove the background from the image. For this image segmentation, we have used the threshold-based method to segment the marigold image. This segmented marigold image is displayed in the figure. (3.4).

3.1.3 Feature Extraction

Feature extraction is the last part of digital image analysis. It is a countable property of an image. CNN automatic features extraction figure is shown in the figure. (3.5). The result of feature extraction is to discover a minimal set of features to analyze an image well enough to differentiate it from another image.

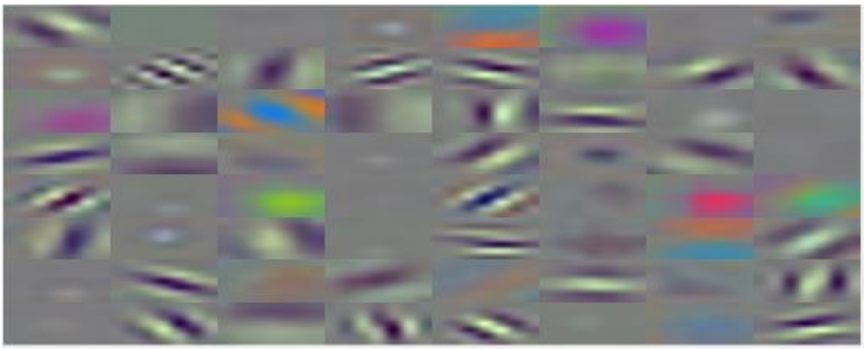

Figure 3.5: Automatic CNN Feature Extraction

The Convolutional Neural Network(CNN) model extracts the image feature in an automatic manner namely image brightness, edge, color, and characteristics. However, other machine learning models are required to extract features for classification and prediction objects.

Table 3.3: Manually and Automatic Feature Extraction and the Description

ML Model	Features Name	Description
ANN, SVM	Average red color	The average value of all red pixels in the marigold maturity level image surface
	Average green color	The average value of all green pixels in the marigold maturity level image surface
	Average blue color	The average value of all blue pixels in the marigold maturity level image surface
	Average hue color	The average value of all hue pixels in HSV marigold maturity level image surface
	Average saturation color	The average value of all saturation pixels in the marigold maturity level image surface
	Average values color	The average value of all values pixels in the marigold maturity level image surface
	Horizontal and Vertical Contrast	Find the local variation of the gray-level co-occurrence matrix
	Horizontal and Vertical Correlation	Find the joint probability occurrence of the specified pixel pairs.
	Horizontal and Vertical Energy	Provide the sum of square elements in GLCM. Also known as uniformity or the angular second moment
	Horizontal and Vertical Homogeneity	Find the closeness of the distribution of elements in the GLCM to the GLCM diagonal.
CNN	Automatic features extraction	The image features are extracted using the activations function.

Here, we have discussed distinct features which are illustrated in (Table3.3). In this work, we have extracted many features namely the average RGV, HSV color of the image surface and those models also have extracted the vertical and horizontal contrast, correlation, energy, homogeneity features to find the local variation, joint probability, provides the sum of squared elements in Gray Level Co-occurrence Matrix (GLCM) and find the closeness of distribution of elements in the GLCM to GLCM diagonal of the of training and testing images.

3.1.4 Image Classification

Image classification classifies the target marigold blooming maturity level class into a predefined input image using a machine learning method. Having being completed the feature extraction, the images are first trained through the machine learning model. When the training process is completed then we have tested a new image of a marigold flower where the image is not used in the training phase. Following, we have seen that our proposed model can accurately classify the blooming maturity level of the marigold. We have evaluated the performance of the ML model classifier by using the confusion matrix(CM). However, in the result section, we have discussed the CM details.

3.2 Machine learning models

Machine learning(ML) is the subset of artificial intelligence(AI). It enables realizing conclusions based on former knowledge without the requirement for human [11] action. The Machine Learning (ML) algorithm is capable of scholarly the former pattern and prophesies the oncoming result after watching. It can resolve the critical problem that involves the large volume of data. The machine learning model extracts suggestive knowledge from the raw data and it resolves the big data-related problems. In this study, we have used several machine learning algorithms like Artificial Neural Network(ANN), Convolutional Neural Network(CNN), and Support Vector Machine(SVM) for the marigold blooming maturity levels classification.

3.2.1 Proposed Artificial Neural Network (ANN) Model

Artificial Neural Network(ANN) is a versed computing system whose central topic is taken from the collateral of the biological nervous [12] system. Our proposed ANN model consists of the input layer, hidden layer, output layer. Each layer construction many neurons. It is also called nodes are simple processors that act together. Each neuron is connected with other neurons through a conjunction link. These neurons presented the normalized feature extracted from the dataset. The internal state of every neuron is called the functional and an activation signal. Output signals that are produced after connected the input signals and functional rule, may be transmitted to other units. Weight is

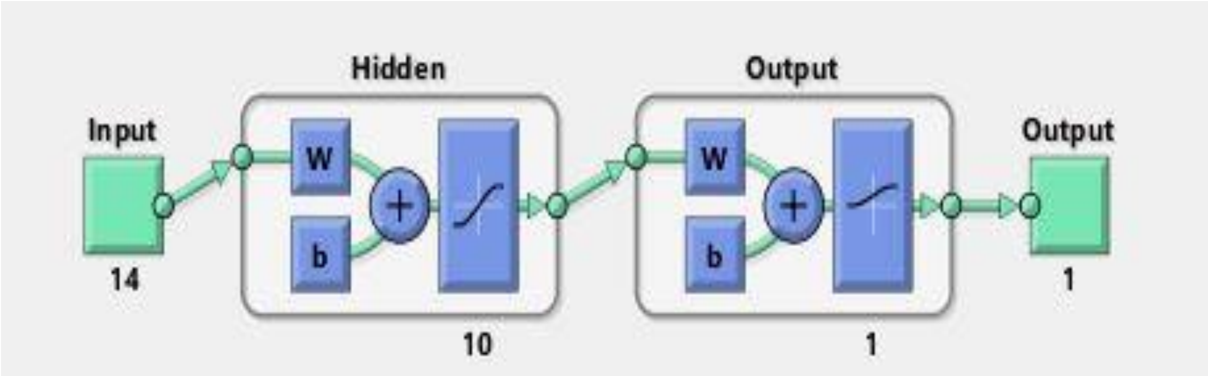

Figure 3.6: Structure of Artificial Neural Network.

combined with each incoming connection from one node to another and each node also has a bias. The weight of input to a node is calculated by equation (3.1) and the block diagram of the proposed ANN model is illustrated in the figure. (3.6).

$Y_{in} = \sum_i^m x_i\, w_i$ … …. … (3.1). where, x_i is the input coming to the neuron, w_i is the connection weight and Y_{in} is the output of the node. The Artificial Neural Network(ANN) is trained frequently to reduce the performance function of mean square error (MSE) between the network outputs and the corresponding target values. At each repetition, the gradient of the performance function or MSE was used to synthesize the network weights and biases. The figure. (3.6) display the imagination of how Artificial Neural Network(ANN) works. The major advantage of ANN is that it can study by itself and generated the output. It is not limited to the input take steps to them. The major drawback of ANN is the duration of the network is unknown and hardware-dependent.

3.2.2 Proposed Convolutional Neural Network(CNN) Model

A Convolutional Neural Network(CNN) is similar to an artificial neural network that also associated the input layer, output layer, and thousands of hidden layers. The Convolutional Neural Network(CNN) to learn obligate representations of features right away from the data. But the main difference is that it uses neurons as the [13] kernel, which are associated with each other and applied over one patch of the input volume. This kernel extracts discrete features from the images such as color, brightness, edges, and the characteristics which are useful to classify the image [13]. The most common layers of the CNN model are the Convolution layer, RelU layer, pooling layer, and fully connected layer. Our proposed Convolutional Neural Network(CNN) method consists of three convolutional layers and fully connected layers for three marigold blooming classes The internal structure of proposed the CNN model is illustrated in the figure. (3.7). All of these layers are described below:

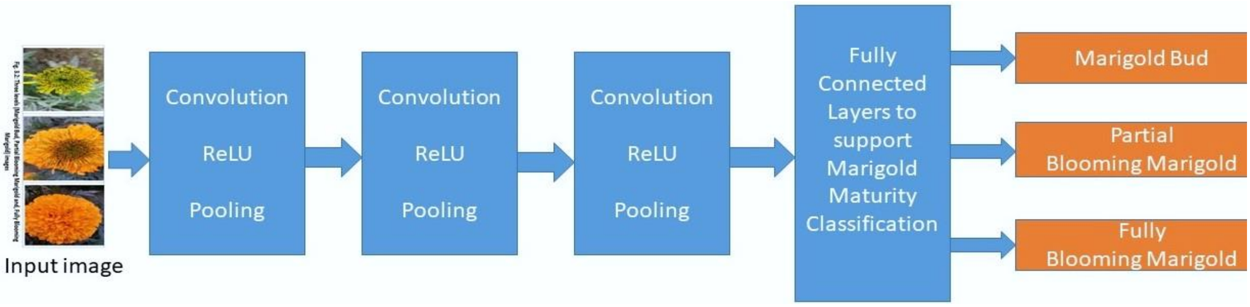

Figure 3.7: Structure of CNN

3.2.2.1 Convolutional Layer

The convolutional layer extracts features from the input images by bringing to bear various filters. This layer is the 3D layers where every neuron computes the multiplication of its weights and input volume of a small region of the previous layers.

3.2.2.2 RelU layer

The ReLU layer also called the rectifier layer that is used as the activation function convolutional layer. The ReLU layer is a non-linear function that computes the linear function namely summation and multiplication of the convolutional layer.

3.2.2.3 Pooling layer

It is the sample-based discretization process. The objective of the pooling layer is to down-sample an input representation(images, hidden layer, output matrix, etc) reducing its dimensionalities assuming for impersonation to constructed about features contained in the sub-region binned.

3.2.2.4 Fully connected layer

It is the last layer of the Convolutional Neural Network(CNN)**.** The result of these previous convolutional layers, ReLU, and pooling layer input into a fully connected layer composition that conducts the final relegation decision. The main convenience of the Convolutional Neural Network(CNN) is to extract features automatically from the training images and the drawback of the CNN model is the required huge amount of data.

3.2.3 Proposed Support Vector Machine(SVM) model

The Support Vector Machine(SVM) is a supervised machine learning algorithm that can be used for classification problems. The primary goal of the support vector machine is to find the hyperplane which divides the two or more classes of data. The schematic block diagram of our proposed (SVM) model is illustrated in the figure. (3.8).

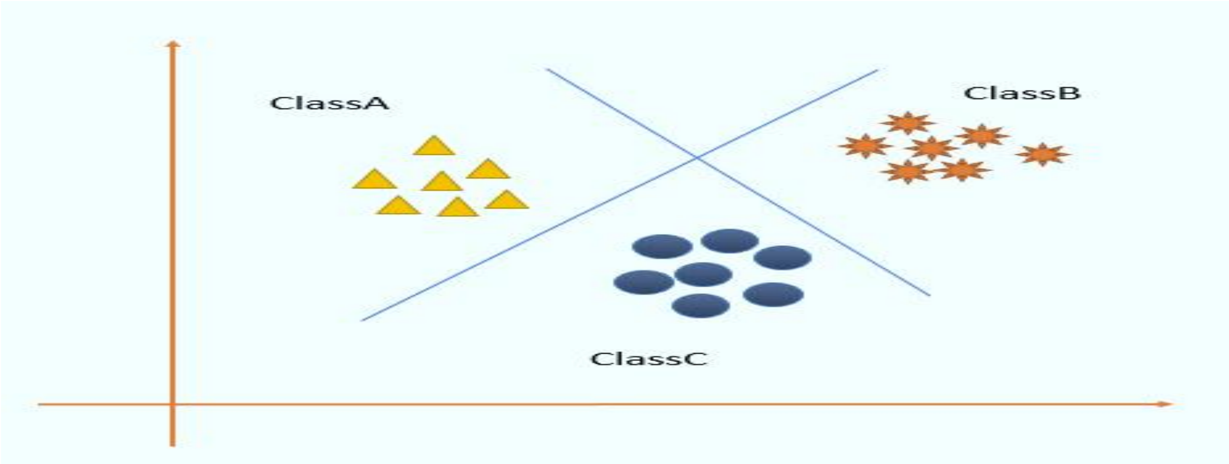

Figure 3.8: Structure of SVM model

The Support Vector Machine(SVM) classifies the object based on the hyperplane in the space[14]. The multi-class data which separate the hyperplane on both sides have a distance to the hyperplane. The smallest distances to the classes are called optimal [14] hyperplane. Given a training set of multi classes, G = {(Xi, Yi), i = 1 … N} with a hyperplane $W^T\phi(x_i) + b = 0$, xi ϵ Rn and y ϵ {1, −1}, the support vector machine satisfies the conditions:

$$(W^T\phi(x_i) + b) \geq 1, if\ yi = 1, \ldots. \ldots \ldots (3.2)$$

$$(W^T\phi(x_i) + b) \leq -1, if\ yi = -1, \ldots \ldots \ldots \ldots (3.3)$$

Or equivalently,

$y_i(W^T\phi(x_i) + b) \geq 1, if\ i = 1,2,3,\ldots \ldots \ldots$ N … … …. (3.4). Where ϕ is the function that maps training vector xi to the higher dimensional space when the data points are linearly separable. The distance from a point xi to the hyperplane is:

$\frac{I(W^T\phi(x_i)+b)I}{||w||^2}$ … … …. …. …(3.5). From the definition of SVM, the margin is $\frac{2}{\|W\|}$. Hence, the equation of hyperplane is $min\ \phi(w) = \frac{1}{2}||W||^2$… … …. ….(3.6)

According to the saddle point of the Lagrange function, the solution of the above equation is, $L_{p1} = \frac{1}{2}||w||^2 - \sum_{i=1}^{n}\alpha_i[y_i(w^T\phi(x_i) + b) - 1]$ … … …. ….(3.7). where αi are the nonnegative Lagrange multipliers. When the data is not separable, a new slack variable ξi is introduced and the optimization equation is: $y_i(W^T\phi(x_i) + b) \geq 1 - \xi_i$ … …. …. …. …. (3.8). And the hyperplane equation is- $min\ \phi(w, \xi) = \frac{1}{2}||w||^2 + c\sum_{i=1}^{n}\xi_I$. .. …. …. …. (3.9). where C is a positive constant parameter used as a penalty parameter for the error term. If the optimization of the support vector machine uses linear and radial basis function, then the equation is: $K(x_i, x_i) = x_{\frac{T}{i}}x_j;\ K(x_i, x_i) = expexp\left(-\gamma||x_i - x_i||^2\right), \gamma > 0$ … … … … … … (3.10), Where γ is the kernel parameter. The figure. (3.8) represents the imaginary view of proposed the Support Vector Machine(SVM) model. The main benefits of the SVM are that it is effective in high dimensional spaces and it also operates the best with a clear margin of separation. The limitation of SVM is that it does not well perform when the data set is too large.

4. Result Analysis and Discussion

In this section, we have compared the performance levels of the Artificial Neural Network(ANN), Convolutional Neural Network(CNN), and Support Vector Machine(SVM) classifier for the marigold blooming maturity levels classification. Now, we have discussed the Confusion Matrix(CM) that is used to evaluate the classifiers. These classifiers are used to predict the marigold blooming maturity levels in our proposed model.

4.1 ANN Classification Result

The Confusion Matrix(CM) is a tabular way of visualizing the performance of our proposed model. Every entry in a confusion matrix represents the number of classifications constructed by the model [15]-[16] where it classified the marigold blooming maturity levels correctly or incorrectly. The confusion matrix of the ANN is produced to assess the performance of the classification model on tested data. The confusion matrix illustrates the total number of proper images per class. We have used a confusion matrix(CM) that provides the accuracy of the classifiers.

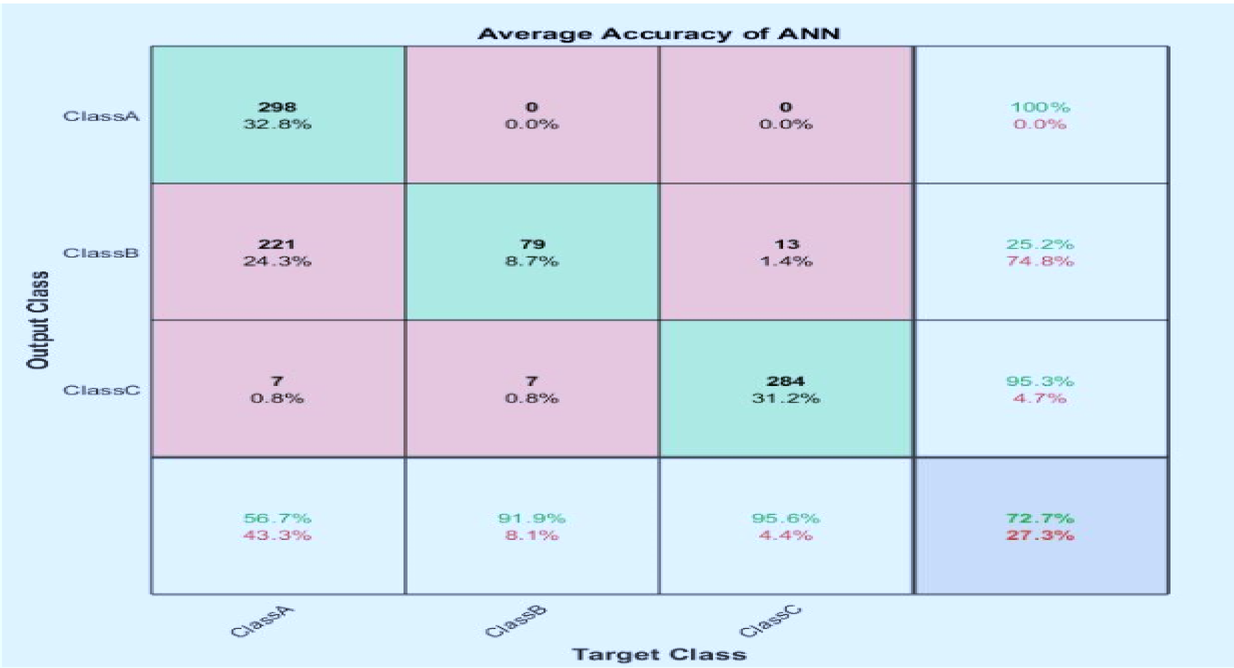

Figure 4.1: Confusion matrix of ANN Model

The classification accuracy is measured as the sum of the proper classification divided by total classifications. In Figure. 4.1, we can see that ClassA is represented a high accuracy than other classes. In the above figure, we see that diagonally shaded boxes depict the percent of accuracy result of the ANN model. On the other hand, the shaded box displays the percent of mistakes for the classification problem. The average accuracy of the classification problem is found to be 72.7%. In this classification, we see that ClasA and (ClassB and ClassC) have the highest and the lowest classification accuracy respectively.

4.2 CNN Classification Result

In this section, we have discussed the convolutional neural network(CNN) classification result. The CNN algorithm classifies the major number of the image are classified with high accuracy. This plot confusion matrix is produced to represent the accuracy labels. Here, the CNN model classifies the total number of images per class. In figure. 4.2, we see that diagonally shaded boxes represent the percent of the accuracy result of the CNN algorithm.

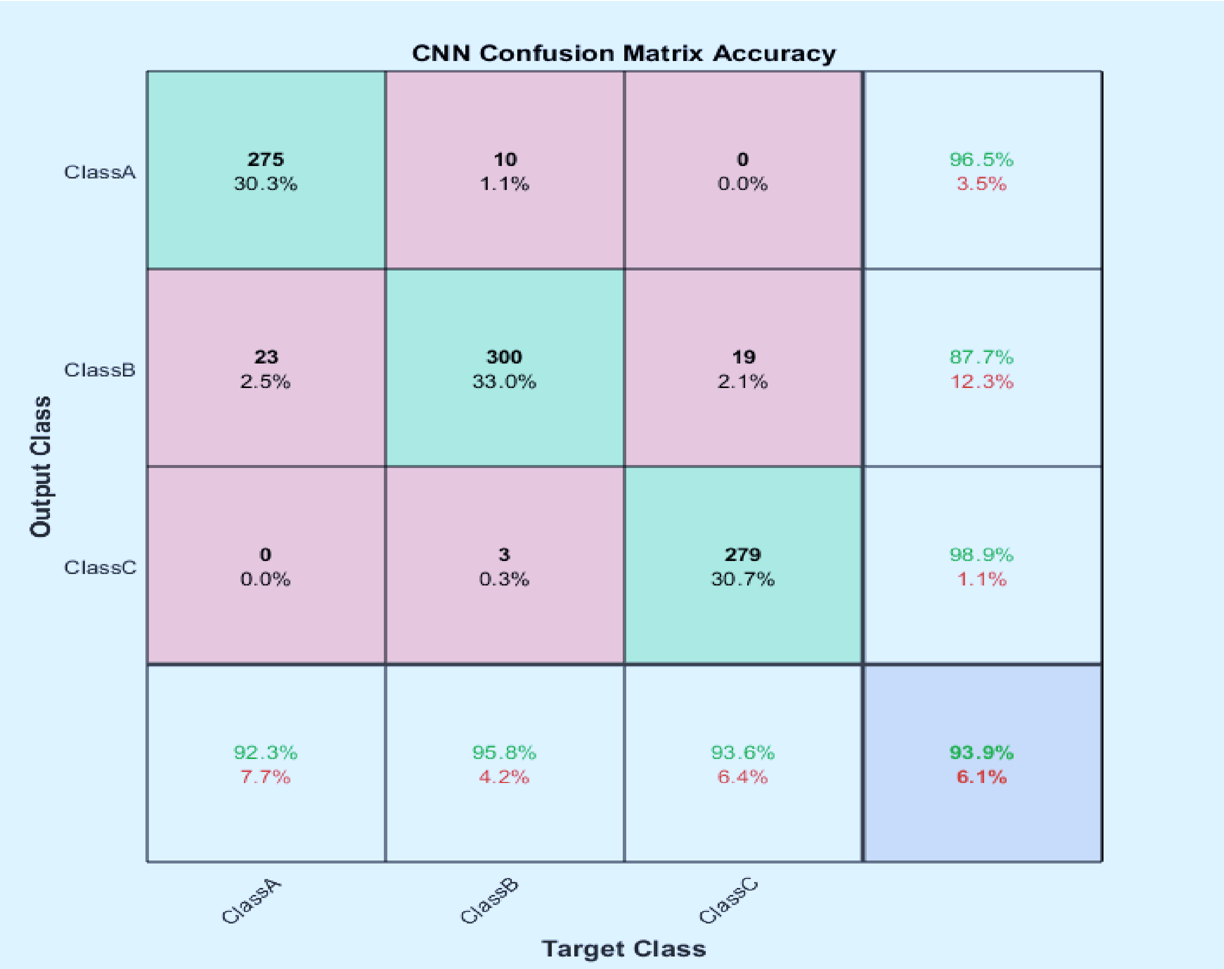

Figure 4.2: Confusion matrix of CNN Model.

On the other side shaded box depicts the percent of mistakes for the classification problem. The average accuracy is displayed of the classification problem is 93.9%. On average mistake is showed in this classification is depicted as 6.1 %. In this classification, we see that the ClassC, and (ClassA, and ClassB) have displayed the highest and the lowest classification accuracy respectively.

4.3 SVM Classification Result

In this section, we have discussed the Support Vector Machine(SVM) classification performance for our marigold blooming ripeness level image classification.

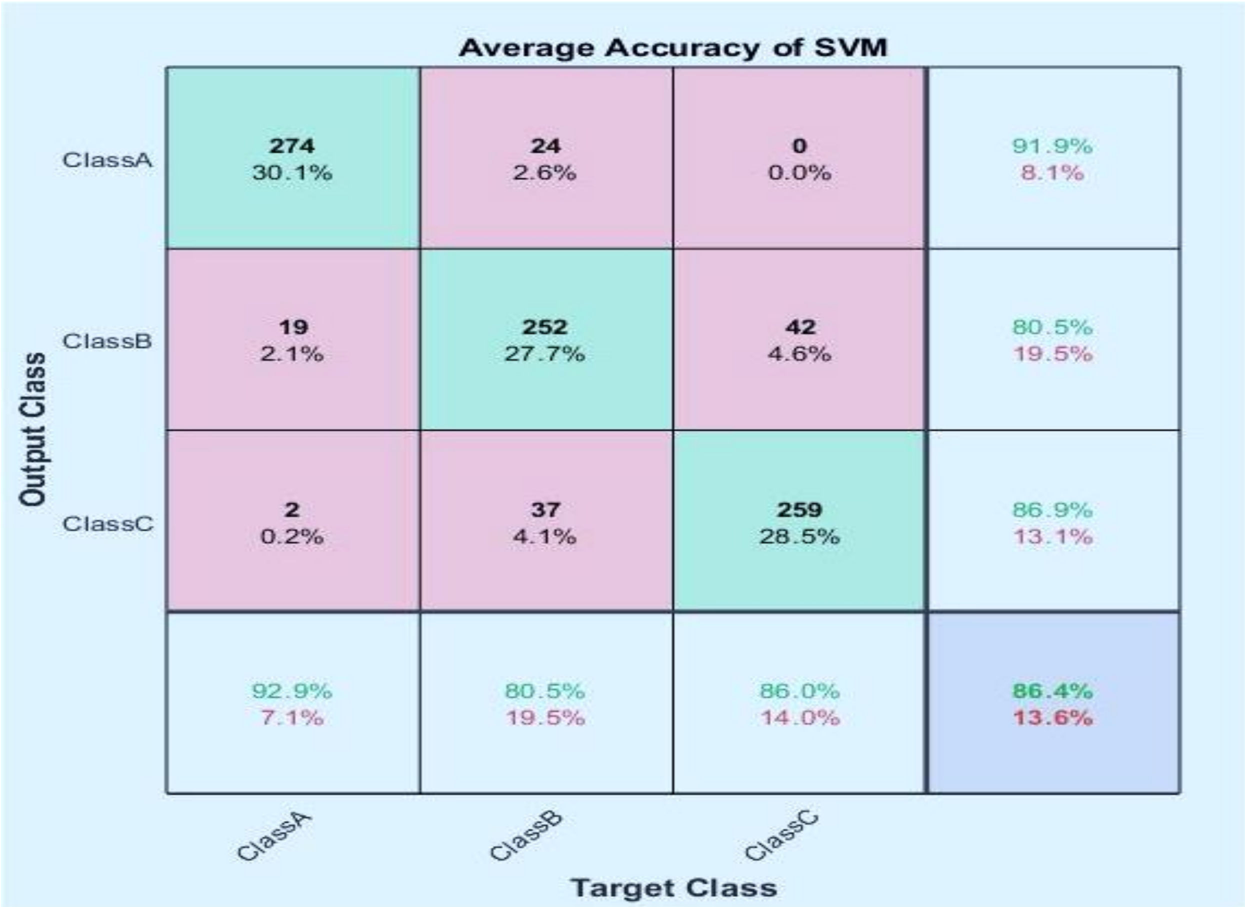

Figure 4.3: Confusion Matrix of SVM Model

In figure.4.3 we see that diagonally shaded boxes display the percent accuracy result of the SVM classifiers. On the other side, the shaded box represents a percent of mistakes for the classification problem. The average validity of the SVM classifier is represented for the classification problem is 86.4% that means the average achievement accuracy for the overall classifier with the best value is 86.4. In average mistake for the overall classifier with the value is 13.6%. In this classification, we see that's the ClassA and (ClassB and ClassC) have shown the highest and the lowest classification accuracy respectively.

4.4 Discussion

From our examination, we have seen the Convolutional Neural Network(CNN) classifier provides the highest accuracy than other machine learning classifiers. On the other side, the Artificial Neural Network(ANN), Support Vector Machine(SVM) classifiers offer low performance than the CNN classifier. Support vector machine(SVM) and Artificial Neural Network(ANN) is depicted low performance when the dataset is large and noisy. In our study, we have used a large image own dataset with three classes of marigold blooming ripeness levels images. The machine learning model to classify the marigold blooming maturity level. Our observation, the Convolutional Neural Network(CNN) algorithm provides higher performance with a large dataset in the other machine learning algorithm. In this study, the Convolutional Neural Network(CNN) classifier has been shown high accuracy more than CNN (93.9%) but low accuracy has been shown in other classifiers such as Support Vector Machine (86.4%), and Artificial Neural Network(72.7%) respectively.

5. Conclusion

In the study, we have provided a novel system to classify marigold blooming maturity level classification using the machine learning algorithm. The proposed system is used machine learning models to automatically classify the marigold blooming maturity level. The proposed system includes four phases: Image pre-processing, Image segmentation, features extraction, and classification. Image Pre-processing phase means resizing the image, noise removal. The segmentation phase aims to remove the flower background. Then, we have extracted various features namely RGB color, HSV color are extracted. Finally, the classification phase can be executed after the feature vectors are produced for every image. Artificial Neural Network(ANN), Convolutional Neural Network(CNN), and Support vector machine (SVM) classifiers are the used machine learning classification algorithms. The proposed system has been done evaluated using 3070 marigold blooming images. From among these images, we have used 70 % images for training and 30% images for testing randomly. From the experimental result, we see that the Convolutional Neural Network(CNN) has achieved the highest accuracy is 93.9% from other Artificial Neural Network(ANN), and Support vector machine (SVM) algorithms. In general, we can say that the Convolutional Neural Network(CNN) classifier provides better accuracy.

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6. Competing interests

The authors have declared that no competing interests exist.

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