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A DEEP LEARNING METHODOLOGY FOR PLANT SPECIES RECOGNITION USING MORPHOLOGY OF LEAVES

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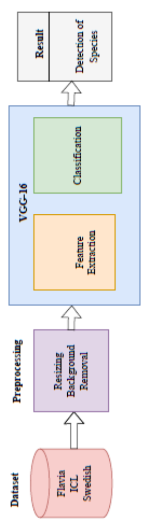
Graphical abstract



Abstract

Plants play a crucial role in supporting all forms of life on Earth, not just humans but every living organism. Understanding the diverse range of plant species that surround us is essential due to their significance in various aspects of human life, including agriculture, the environment, medicine, cosmetics, and more. Advancements in machine learning and computer vision algorithms have opened possibilities for identifying different types of plant species, both within and across classes. Plant species detection typically involves several steps, such as image acquisition, feature extraction, categorization, and pre-processing. In this study, three datasets—namely Flavia, Swedish, and the intelligent computing laboratory (ICL) dataset—were chosen for experimentation purposes. For feature extraction, three different models were employed: k-nearest neighbour (KNN), naive Bayes (NB), and the visual geometry group (VGG)-16 model. These models were used to extract distinctive features such as shape, texture, venation, and margin from the plant images. A multiclass classification task was conducted to categorize the plant species. Among the models tested, the VGG-16 model consistently demonstrated superior performance in terms of accuracy. Specifically, when using the VGG-16 model, the obtained accuracies were 96.68% for the Flavia dataset, 97.65% for the Swedish dataset, and 96.11% for the ICL dataset.

Keywords: KNN, NB, VGG-16, Flavia, Swedish, ICL

1.0 INTRODUCTION

Species identification of plants has been a significant area of research in the fields of ecology and biological evolution [1]. To accurately identify distinct characteristics within and between species, researchers have sought more precise systems, as manual identification methods can be laborious. As a result, various machine intelligence approaches have emerged, offering automated solutions for species identification [2-4]. Accurate skills are crucial in many activities such as environmental research, ecology, farming, and assessing the impact of environmental conditions on different species. Researchers have employed complex techniques including computer vision, bilateral convolutional neural networks (CNNs), and machine learning methods, which can be challenging for ecologists to comprehend [5-7]. An efficient framework is crucial for species identification as it facilitates algorithmic development and automation in species recognition [8]. It should be capable in automation identification processes [9]. Deep learning has emerged as an active field of study in agriculture [10]. One of the significant impacts of deep learning lies in its effective feature extraction methods. Manual feature extraction processes require extensive expertise in the agricultural and ecological domains, and they are also time-consuming [11-15].

Numerous studies have focused on plant identification using different plant parts such as bark and flowers. However, leaves are considered more prominent in plant identification due to their distinct features [4-6,11,12]. Leaves possess essential characteristics like texture, color, margin, and shape, which play a vital role in species identification.

To effectively capture these intricate leaf features, several models have demonstrated superior performance. Models such as visual geometry group (VGG)-16, AlexNet, Xception, DenseNet, and CNN have consistently shown remarkable results in plant species identification [5, 12].

Plant species automation for detecting medicinal plants is in trends for researchers. A wrongly selected herbal plant may lead to severe health problem if the species is misclassified. To avoid this manual misclassification automated system, need to be developed. For this study [16] have considered multilateral and texture features and applied CNN for extraction of features. For the detection of plant species roots, stem, bark, fruits, and flowers could be considered. But more distinct features can be extracted using leaf because comparing with other plant organs, leaves have a longer lifespan. It has various features as shape, texture, colour, venation, margin, petiole, patches etc., which makes it more useful organ in this study [17]. The challenging aspect in species recognition is the ability to accurately differentiate between closely related species or individuals with similar characteristics [18-20]. This requires developing algorithms and models that can effectively distinguish subtle differences and variations within species, while also handling variations in lighting conditions, image quality, and environmental factors [18-20].

This issue can be addressed by combining multiple features, including leaf length, size, shape, apex-to-petiole ratio, eccentricity, convex hull, and contour. Hybridizing these features can potentially yield more accurate results compared to using a single feature extraction method [21].

To handle the complexities of vegetation patterns in plant detection, CNNs need to be enhanced or hybridized. Several studies have demonstrated the effectiveness of CNNs in analyzing RGB real-life images and images captured by unmanned aerial vehicles (UAVs). To explore the capabilities of CNNs further, the authors of this study utilized real-life datasets obtained from aerial UAV imagery, deviating from using the same dataset typically employed [22].

In previous research work invasive alien plants (IAP) in wild were identified by manual inspection of aerial images which was cost effective. At the same time, it covered a very small area for capturing UAV images. On the other hand, satellite based captured images covered a larger area with accurate images. IAPsNet was proposed to detect such distinct varieties of plants in wild areas by [23]. By observation, it has been concluded that leaf is more prominent organ on which best CNN model can be applied. The generated features form this model were classified and accurate, automated species of plants was detected. In this article k-nearest neighbor (KNN), naive Bayes (NB) and VGG-16 model, was applied to Flavia, Swedish and intelligent computing laboratory (ICL) dataset.

The objectives of this paper are as follows:

- To apply the KNN, NB, and VGG-16 models for extracting leaf features.
- To utilize multiple classifiers for species classification based on the extracted features.

This paper is organized as follows: Section 2 provides a comprehensive literature review. Section 3 explores and discusses the methods employed in this study. Section 4 presents the results and discussion of the findings. Finally, Section 5 concludes with a summary and closing remarks.

2.0 LITERATURE REVIEW

Leaf tips and leaf margin were key factors considered in this study [24, 25]. The authors also explored the use of context-based shape descriptors, including the leaf margin value and the spatial relationship between the leaf and its margin. To obtain results, a combination of these two technologies was employed, utilizing the leave-out algorithm [25].

In their work, Ren et al. (2015) [26] introduced a novel moving median centre hypersphere classifier. Their study involved a comparison of their results with those obtained using 1- (neural network (NN) and KNN classifiers [27]. The authors demonstrated that their proposed system exhibited higher efficiency compared to other comparable methods.

Some of the well-known deep learning architectures used for categorization includes VGG-19, ResNet, GoogLeNet, AlexNet, Inception V3, VGG-16 [28]. A deep learning model can be chosen for a specific application based on a variety of factors. The state-of-the-art deep learning models' performance has been thoroughly researched and compared with allowing a model to be chosen for use in real-world applications [29].

It is also important to note how the input data sample and inference time in deep learning architecture varies depending on the batch size. Deep learning models that are ideal for real-time and resource-constrained applications have a short inference time, a small number of operations, and minimal power consumption [30].

Different architecture of AlexNet have also been discussed with its layers [31, 32]. It also coverd the kernel size resulting responses are normalized and subjected to overlapping pooling to generate a summarized mapping for the evaluation.

In [33] Kan et al. (2017) proposed a method by combining discrete wavelet transform (DWT), multi resolution transform and grey level co-occurrence matrices (GLCM) for measuring the morphology of leaf teeth. For this experiment they did not consider the texture and shape of leaves. In this experiment they got an accuracy up to 88.25 %.

The proportion between leaf lengths to its width, known as the major axis length, was computed [34]. They calculated ratio by calculating major teeth of leaf and length of leaf. Furthermore, their approach involves calculating each leaf margin's sharp angle.

The application of deep learning has proven to be effective in accurately identifying plants by capturing important leaf traits [34]. Another study [20] demonstrates that the problem of weak convergence and generalization. It has been discussed when deep learning algorithms have been used. Deep learning algorithms surpass general classification algorithms that rely on features such as color, shape, and texture, resulting in improved performance.

A novel CNN model called D-leaf was introduced [35]. Feature extraction was carried out using D-Leaf, tuned AlexNet, and AlexNet models. Various classifiers, such as support vector machine (SVM), KNN, artificial neural network (ANN), NB, and CNN, were employed for character classification. The accuracy of the proposed approach ranged between 90% and 98% on multiple datasets, including Flavia, Swedish, and MayaKew.

In their work [36], Milioto et al. (2018) presented a method for the identification of Ayurvedic medicinal plants utilizing a dataset consisting of real captured images of Ayurveda plant leaves. The authors employed a combination of geometric, color, and texture-based Zernike features [37]. This approach aimed to identify specific combinations of leaf color, texture, and morphology that would enhance the recognition accuracy for green leaves.

Researchers can differentiate between various traits, developmental stages, or plant types by analyzing the characteristics of the plants. In the study conducted by [38], they extracted important properties such as aspect ratio, vertical eccentricity, rectangularness, leaf type, horizontal symmetry, and representation. Their approach focused on visual consistency and the complexity of the leaf's lamina. Furthermore, they computed the distance between these features using B-spline to facilitate the identification of occluded leaves.

In their study [39], Pereira et al. (2019) utilized natural vineyard image datasets containing six grape species collected from various locations. They proposed a four-corners-in-one image warping technique and applied transfer learning using a pre-trained AlexNet model for feature classification. Their approach achieved results with an accuracy of up to 89.75%.

In their work [10], Kaya et al. (2019) proposed the use of AlexNet and VGG16 models with transfer learning for species identification. They compared the performance of these models with fine-tuning and found that they achieved better results compared to transfer learning alone. They applied SVM and local discriminant analysis (LDA) for classification on four datasets.

In their work [23], Qian et al. (2020) proposed a 40-layer deep CNN called IAPsNet, which was based on LeNet, VGG, AlexNet, and GoogLeNet architectures. They collected a dataset of 6400 images using an unmanned aerial vehicle (UAV), which was divided into 8 groups of IAPS. The IAPsNet model was trained and evaluated under various environmental conditions, and they achieved an accuracy of 93.39% with minimal loss.

In [40], Pushpanathan et al. (2021) performed leaf augmentation on plant which showed strong consistency in laminas with little variation. Substantial difference has been observed when different features considered like shape, complexity, and aspect ratios.

In [41] Yang and Wei (2019) represents a two-stage deep model time-domain Reflectometer (TDR). It consists of two matrices as a matrix of signs and a matrix of the triangle's centre distances. The former has been used to define the convex or concave quality of a shape, while the latter has been used to express the degree of bending and shape relative to the spatial aspects of the contour of the shape. Translation, rotation, and scaling transformations were used to perfectly capture the overall properties of leaf shape without loss of data [42].

In [6], Sohn et al. (2021) proposed a near-infrared spectroscopy approach along with the machine intelligence approaches for leaf species detection. Various conventional machine learning algorithms are applied for feature extraction out of which Savitzky-Golay pre-processing and SVM performed better with an accuracy of 99.7%.

In their work [12], Wagle et al. (2021) proposed a deep learning algorithm that utilizes graphs and incorporates linear and nonlinear transformations for data abstraction. They highlighted the suitability of CNNs for feature extraction and classification in plant species classification tasks. CNNs are well-suited for this task due to their ability to capture relationships between layers and exploit spatial information.

In their study [16], Naeem et al. (2021) utilized herbal datasets containing leaves of neem, Tulsi, and other plants. They employed Sobel filters for edge and line detection. The extracted features were then optimized using the chi-square feature selection method, resulting in 14 optimized features. For classification, the researchers applied multiple algorithms including multi-layer perceptron, logistic regression with boosting, bagging, random forest, and simple logistic regression. The results showed that the multi-layer perceptron achieved the highest accuracy of 99.01%.

In [43], Hati and Singh (2021) made use of imbalance dataset. The number of images is not the same for each class labels. After performing pre-processing on images. Resnet20 and multiclass classifier were applied for feature extraction and classification respectively. They achieved an accuracy of 92%.

In [44], Ibrahim et al. (2022) proposed novel CNN on 52 families of fruits having 3800 images having 10 layers where algorithm performed 200 epochs. For classification SVM was used on both small and large datasets. The results were fluctuated by +/- 0.39 and +/-0.17 using small and large dataset respectively. The performance got increased using SVM giving an accuracy of 93%.

In [45], Barhate et al. (2022) used hyper parameter tuning and principal component analysis for simplifying data. CNN is trained on Flavia dataset which gave accuracy up to 99%. The results are compared with some traditional approaches out of which CNN methodology worked better.

Variably overlapping based approach using sliding window was presented by Abdalla et al. (2022) in [46]. This transformed the images into 3D images. Two algorithms were hybridized namely VOTCSW and 1-dimentional polynomial neural network. By using this approach, they have reached an accuracy up to 99.9% on dataset having 40000 images.

In [47], researchers explored and compared various deep learning-based approaches for their preferred choice. Four types of deep learning models were considered: CNN, deep belief networks (DBN), recurrent neural networks (RNN), and stacked autoencoders. These models have gained significant popularity in the field of deep learning due to their effectiveness in handling complex and high-dimensional data.

3.0 MATERIALS AND METHODS

Three datasets, namely Flavia, Swedish, and ICL, were utilized for the experiment.

The Flavia dataset [48], comprises 1907 images of 33 different plant species. Some of the species included in this dataset are true indigo, plum pine, Chinese Tulip, Chinese Toon, and others. The images in this dataset are clear and have a white background, with the absence of the stem. Figure 1 showcases some samples from this dataset.

The Swedish dataset [48], consists of 75 samples for each plant species. In total, there are 15 different plant species included in this dataset. It comprises a total of 1125 leaf images, all of which have a white background and include the stem. Some of the species included in this dataset are Acer, Populus, Tilia, Quercus, and others. Figure 2 displays a few samples from this dataset.

The ICL dataset [49], consists of 16,848 images representing 220 different species of leaves. The images in this dataset are horizontally oriented and have a white background. Some images include the stem, while others do not. Figure 3 showcases a few samples from this dataset.

The experimental workflow of the entire study is illustrated in Figure 4, encompassing various stages such as data collection, dataset division into training and testing sets, model evaluation metrics, classifiers, and outcomes. The experiment was conducted using the Flavia, Swedish, and ICL datasets, with pre-processing steps including augmentation and background removal. VGG-16 model was also used and the main purpose it to perform the feature extraction.

To compare the classification results, KNN, NB, and CNN classifiers were employed. The evaluation metrics considered for comparison and experimentation included accuracy, precision, recall, and F1 score. Ultimately, the system provides output in the form of plant species names along with their scientific names.

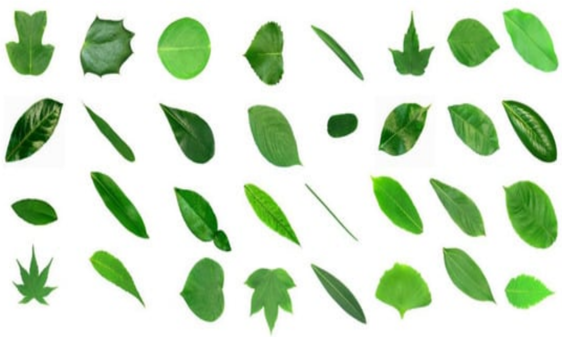


Figure 1 Samples of Flavia dataset [48]

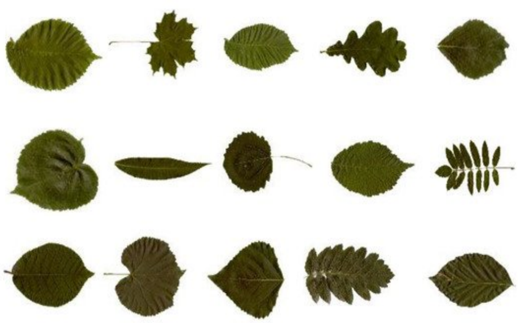


Figure 2 Samples of Swedish dataset [48]

Figure 3 Samples of ICL dataset [49]

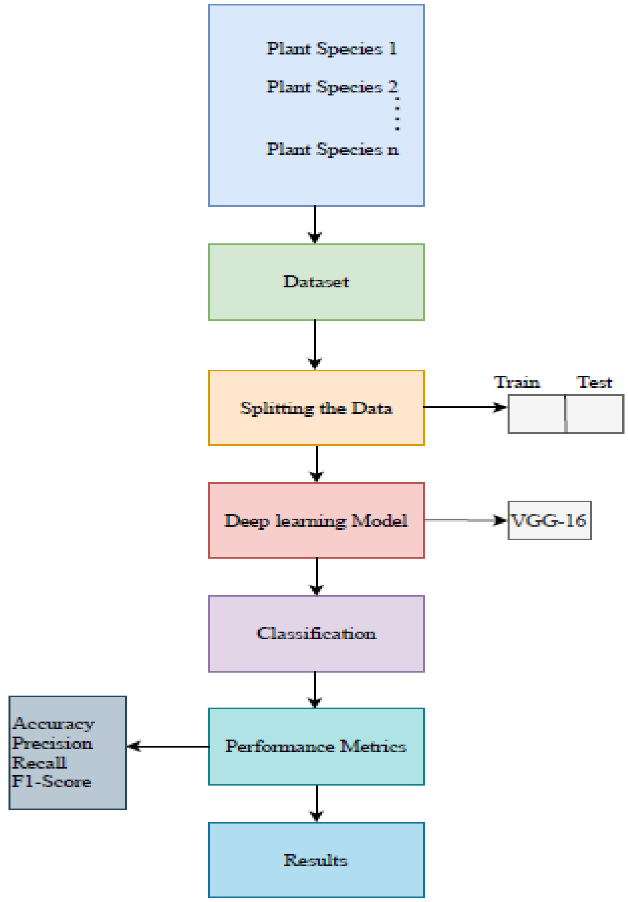


Figure 4 Flow diagram of model

The system architecture is depicted in Figure 5. The initial step involves dataset collection. For this experiment, three datasets—Flavia, Swedish, and ICL—were utilized. The dataset images undergo pre-processing, which includes background removal, augmentation, resizing, cropping, and transformation. After the processing of each image, it is passed through the VGG16 module for feature extraction and classification.

The VGG-16 model employed in this study comprises five convolutional layers. Its utilization is based on its capability to provide diverse representations. Figure 6 presents a visual representation of the VGG-16 configuration, outlining its specific details. To facilitate the experimentation, the dataset was divided into a training set and a testing set. The ratio used for this division was 70% for the training set and 30% for the testing set, as depicted in Figure 6.

The aim of this experiment is to apply an accurate learning model for the detection of plant species. The VGG-16 model used in this experiment consists of a total of 1,630,160 trainable parameters, as depicted in Figure 7. The images used for the experimentation are colored RGB leaf images.

The input size to the model is (73×73×64). VGG-16 architecture reduces hyper parameters by utilizing convolutional layers with a variable filter size of 5×5, 4×4 and 3×3 and a stride of 1. The selected size for comparative analysis was 3×3. The max pooling layers employ a variable filter size of 4×4, 3×3 and 2×2 with a stride of 2. The selected size for comparative analysis was 2×2.

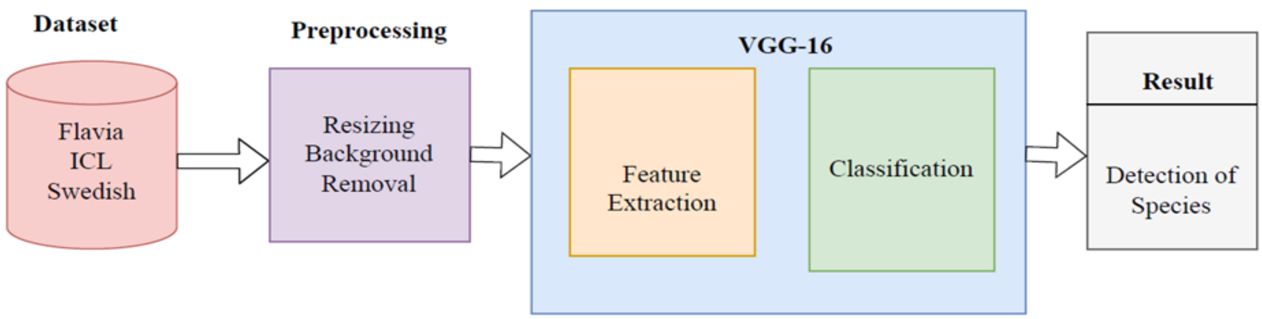


Figure 5 Architecture of model and step by step procedure

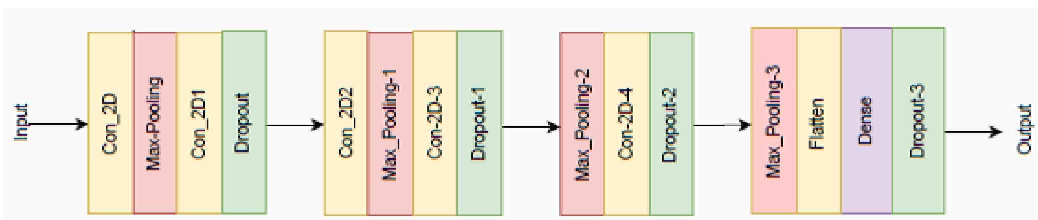


Figure 6 CNN layer for plant species identification

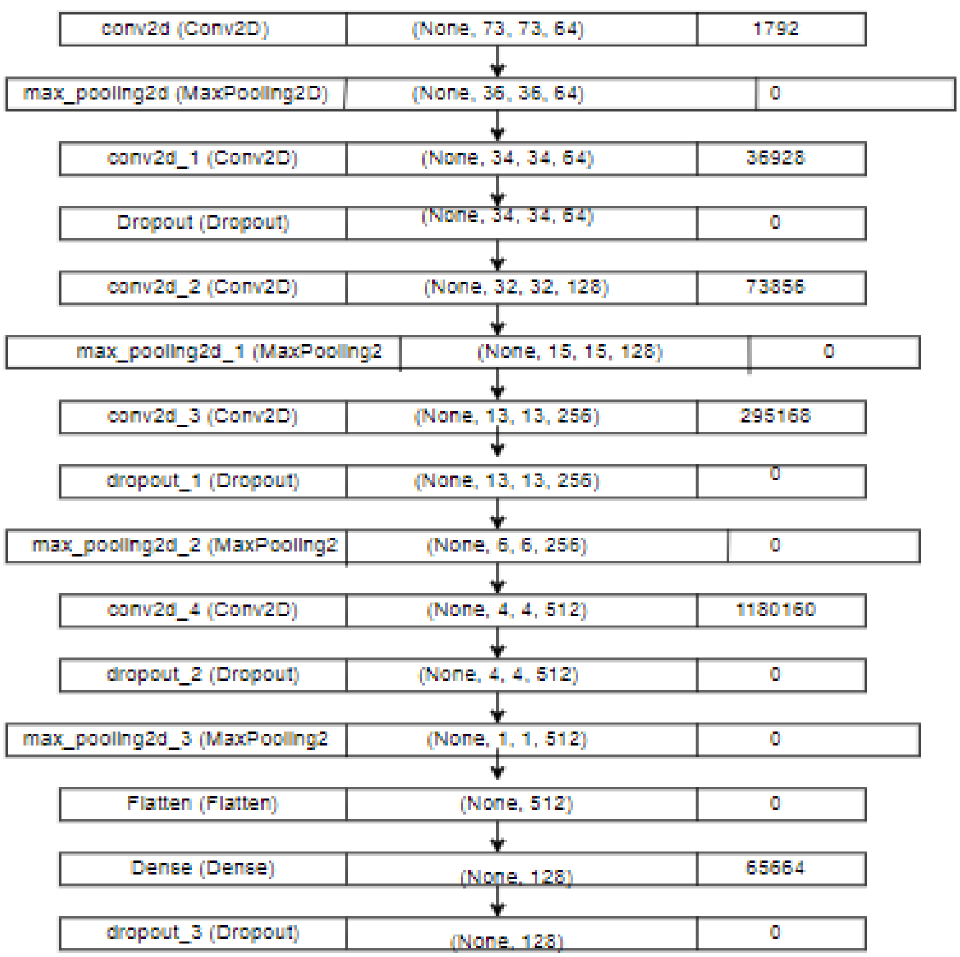


Figure 7 CNN specification with its layers and parameters

After extracting RGB images, they were independently trained and evaluated using the VGG-16 model. The features extracted are texture, shape, margin, venation, and size. Flatten and dense layers of VGG-16 were used for the feature extraction and classification of the extracted features. It enables the multiclass classification. This process determined the species of each image. Throughout the system, the pairing of convolutional layers and max-pooling layers was maintained.

After passing through the flatten layers, the output was transformed. It has been transformed from the 28×28×64 and 28×28×32 output. These output vectors were processed for the classification. Dense layer was considered for the processing considering the output vector as the input.

The model consisted of five convolutional layers. It covers the range of max-pooling layers which is between 4-7, in our case four has been considered. SoftMax function was also been considered and a flatten layer. The input to this model was 75×75×3. The output vectors from the flatten layers condensed the 73×73×64 and 73×73××32 output into one dimension vector. These output vectors were processed for the classification. Dense layer was considered for the processing considering the output vector as the input. Feature extraction using VGG-16 was performed by utilizing the convolution blocks (pair of conv1 and conv2), and the results were sent to the pool 1 max-pooling layer.

4.0 RESULTS AND DISCUSSION

The performance matrix used in this paper is as follows.

- True Positive (A): these are the samples which are labelled accurately by the classifier.
- True Negative (B): These are Negative samples labelled correctly.
- False Positive (C): These are negative samples labelled correctly.
- False Negative (D): these are positive samples labelled negative incorrectly.

These parameters are then used for calculating Recall, Precision, F1-Score and Accuracy as follows:

The True positive rate is known as Recall(R).

Recall=A/A+D

The model applying positive samples to positive classis precision (p).

Precision = A/A+C

F1-score is harmonic mean of precision and recall

F1score = 2×P×R / P+ R

Accuracy is correct prediction-based on the above performance parameters

Accuracy =A + B / A + B + C + D.

The experimental results demonstrate that the proposed system outperformed conventional existing methods in accurately detecting plant species. Three classifiers, namely KNN, NB, and CNN, were applied to the three different datasets. The accuracy results obtained were as follows:

For KNN: The accuracies were 80.09%, 75.13%, and 81.49% on the Flavia, Swedish, and ICL datasets, respectively.

For NB: The accuracies were 72.12%, 72.18%, and 69.85% on the Flavia, Swedish, and ICL datasets, respectively.

For CNN: The accuracies were 91.56%, 92.45%, and 91.6% on the Flavia, Swedish, and ICL datasets, respectively.

However, the experimental method using the VGG-16 model achieved even better results compared to these methods. The accuracies obtained were 96.68%, 97.65%, and 96.11% on the Flavia, Swedish, and ICL datasets, respectively. The results of computations based on the performance parameters are presented in Figure 8-Figure 11, showing that VGG-16 achieved the highest accuracy among KNN, NB, and CNN for all the performance parameters. Overall, the results demonstrate that the proposed VGG-16 model significantly improved the accuracy of plant species detection compared to the other classifiers used in the experiment.

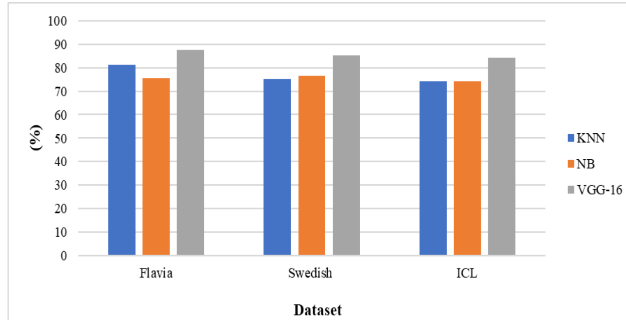


Figure 8 Comparison of precision using the KNN, NB, and VGG-16 methods on the Flavia, Swedish, and ICL datasets

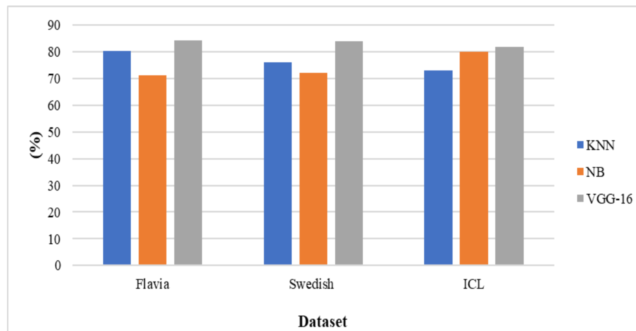


Figure 9 Comparison of recall using the KNN, NB, and VGG-16 methods on the Flavia, Swedish, and ICL datasets

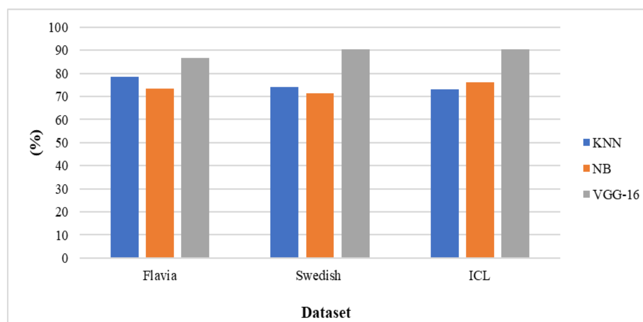


Figure 10 Comparison of F1-score using the KNN, NB, and VGG-16 methods on the Flavia, Swedish, and ICL datasets

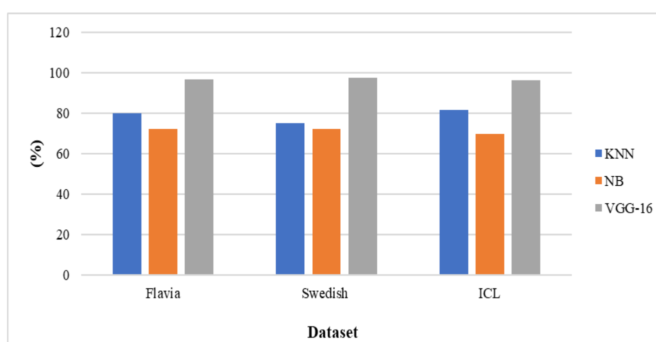


Figure 11 Comparison of accuracy using the KNN, NB, and VGG-16 methods on the Flavia, Swedish, and ICL datasets

In order to evaluate our model, we compared it with various deep learning models used by different researchers such as residual neural network (RNN) with 20 layers (ResNet-20), SVM, and CNN, using the same dataset. On the Flavia dataset, our proposed VGG-16 model achieved an accuracy of 95.32%, outperforming the ResNet-20 (90.78%), SVM (92.32%), and CNN (92.59%). Similarly, on the Swedish dataset, our VGG-16 model achieved an accuracy of 94.46%, surpassing the ResNet-20 (93.13%), SVM (95.18%), and CNN (94.85%).

Furthermore, we compared our results with other classifiers such as NB, KNN, classification and regression tree (CART), and random forest (RF). Our VGG-16 model exhibited superior performance with an accuracy of 96.68%, while the NB, KNN, CART, and RF classifiers achieved accuracies of 95%, 94%, 92%, and 93% respectively. The detailed accuracy comparison analysis is shown and depicted in Table 1.

Table 1 Analysis of results based on different approaches and the proposed VGG-16

Datasets	RNN[44]	ResNet-20 [44]	SVM [44]	CNN [44]	VGG-16
Flavia Dataset	90.78	92.32	92.59	95.32	96.68
Swedish Dataset	93.13	95.18	94.85	94.46	97.65
	NB [5]	**KNN [5]**	**RF [5]**	**CART [5]**	**VGG-16**
Flavia Dataset	95	94	92	93	96.68

The current system successfully identifies the correct species of plants in real-life scenarios. However, there are certain limitations that can be addressed in future enhancements. One such limitation is the system's inability to detect occluded leaves, where leaves may be partially covered or hidden from view. This can be an area of improvement to make the system more robust in handling occluded leaf images. Furthermore, the scope of the system can be expanded to include the detection of weed species among plants. Weed identification is an important task in agriculture and horticulture, as weeds can have detrimental effects on crop growth and yield. By incorporating weed species detection, the system can provide additional value and assist in weed management strategies. Overall, future improvements can focus on addressing these limitations and expanding the system's capabilities to enhance its performance and applicability in plant identification tasks.

5.0 CONCLUSION

In this paper, the recognition of plant species using a deep learning model was performed on three open-source datasets: Flavia, Swedish, and ICL. The images were pre-processed and then inputted into the VGG-16 model. The slit-ratio considered was 70-30 ratio. The results indicated that the proposed models performed better on the Swedish dataset, achieving an accuracy of 97.65%, compared to the Flavia and ICL datasets, which achieved accuracies of 96.68% and 96.11%, respectively. Additionally, the method demonstrated effectiveness in dealing with unbalanced datasets. The presented solution in this paper provides a viable approach for addressing the challenges of plant species identification. In future research, hybrid methods and classification techniques may further enhance the recognition of plant species through multi-feature fusion extraction.

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