An Efficient Computer Vision Approach for Rapid Recognition of Poisonous Plants by Classifying Leaf Images using Transfer Learning

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***Abstract*— Livestock poisoning by several kinds of poisonous plants causes grievous economic losses to the livestock industry. Poisonous plants are also a fatal threat to humans, ingesting these plants can cause several side effects in the body because of their toxicity. Hence, it is essential to develop a rapid approach to recognize poisonous plants efficiently. This paper addresses a recognition approach for eighteen poisonous plants using poisonous plants leaf (PPL) dataset which has been generated using image augmentation techniques that contains 54000 training, 27000 validation, and 9000 testing images. Six different state-of-the-art deep learning models have been used in this study such as Xception, ResNet152V2, InceptionResNetV2, MobileNetV2, DenseNet201, and NASNetLarge for classifying leaf images of poisonous plants. Xception has shown more significant performance than other models, achieved 99.71% training and 99.37% testing accuracy. NASNetLarge and InceptionResNetV2 have achieved 96.89% and 95.18% test accuracy, respectively, and MobileNetV2 achieved the lowest test accuracy.**

Keywords—Deep Learning, Transfer Learning, Xception, Poisonous Plants Recognition, Depthwise Separable Convolutions

I. INTRODUCTION

Plants are very crucial for all living things but poisonous plants cause a severe economic loss to the livestock industries all over the world, and toxins of these plants are also dangerous for humans [1]. Ingesting poisonous plants causes burning of the mouth, skin irritation, diarrhea, headache, blurred vision, nausea, arrhythmia, dizziness, tremors, and many other diseases [2]. A remarkable number of poisonous plants are grown throughout the world, and rosary pea, sugar apple, mexican prickly poppy, itchytree, giant calotrope, hashish, colocynth, dodder, moonflower, oleander, blue plumbago, crepe jasmine, philodendron, arrowhead, dumb canes, caladium, golden pothos, and stinging nettle are commonly seen poisonous plants in many countries. Rosary pea is native to Australia and Asia, seeds of this plant contain abrin which is a highly toxic toxalbumin that can be deadly for humans and animals. Seeds of sugar apple are extremely poisonous, dried fruit and powder of seeds are used as insecticide and fish poison in India. Mexican prickly poppy has extremely dangerous toxin characteristics which contains isoquinoline alkaloids and almost all parts such as bark, flowers, fruits, leaves, roots, seeds, and stems are highly poisonous. Fruits of itchytree are poisonous, and this plant is generally grown in Southern Asia, and Northern Australasia. Giant calotrope contains calotropin which is a toxic cardenolide that causes respiratory and cardiac failure. Flower stalks of hashish are highly poisonous [3]. Colocynth has some toxic side effects and causes gastrointestinal disorders. Dodder is harmful to horses, affects the liver and nervous system of horses, and absorbs poisons from the host plants. All parts of the moonflower are toxic which contains a threatening level of tropane alkaloid, ingesting this plant can cause anticholinergic effect, tachycardia, hallucinations, nausea, and diarrhea [4]. Flower, leaf, stem, and twig of oleander contain toxic ingredients such as digitoxigenin, neriin, oleandrin, and oleondroside, and poisoning of this plant affects almost all parts of the body. Blue plumbago irritates the eyes and skin, and fruit, seed, and root of this plant are toxic. Crepe jasmine contains more than 66 different types of alkaloids, and almost all parts of it are toxic [5]. Philodendron, arrowhead, dumb canes, caladium, and golden pothos are poisonous houseplants, and these plants can be a danger to pets and children. Stinging nettle causes severe skin irritation, and is highly toxic for pets.

A remarkable number of researchers have achieved significant success in different object recognition related tasks such as skin disease recognition, inflammatory food recognition, and leaf disease recognition by using state-of-the-art convolutional neural network (CNN) models with the transfer learning approach [6] [7] [8]. During training, CNN models need a large number of images to attain a satisfactory performance. An image dataset of 90000 images of eighteen poisonous plants has been generated using different image augmentations techniques. Xception has achieved 99.37% accuracy at recognizing eighteen different types of poisonous plants, and the architecture of this model was built with depthwise separable convolution layers [9]. The performance of Xception was compared with five other pre-trained CNN models in this study such as ResNet152V2, InceptionResNetV2, MobileNetV2, DenseNet201, and NASNetLarge. The outcome of this study will be highly beneficial for the livestock industry, and it will help farmers to reduce the severe economic loss that occurs for poisonous plants. Moreover, humans, especially children, can ensure their safety from poisonous plants using the proposed approach, and the major contributions of this paper are summarized as follows:

- To the best of our knowledge, this is the first attempt to establish an efficient computer vision approach for recognizing poisonous plants using deep learning.
- An image dataset of eighteen poisonous plants leaf, namely, PPL, has been created for the generalization of state-of-the-art CNN models that contain 90000 images with uniform and complex backgrounds.

- The recognition performance of different pre-trained CNN models have been analyzed using 9000 images of the test set of the PPL dataset for rapid and accurate recognition of poisonous plants.

The rest of this paper is organized as follows: Related work introduces and summarizes in Section II. Section III describes the PPL dataset, and state-of-the-art deep learning models used in this study. Experimental studies are presented in Section IV. The results obtained in this study are presented and discussed in Section V. The study is concluded with Section VI.

II. Related Work

With the continuous development of computer vision based machine learning and deep learning approaches, researchers have been broadly utilized these approaches to recognize leaves of different plants.

Hulya Yalcin et al. have used CNN to classify 16 kinds of plants and achieved 97.47% accuracy [10]. The performance of CNN has been compared with the performance of the support vector machine (SVM). Using radial basis function (RBF) kernel with fusion feature, SVM has achieved 89.94% accuracy. On the other hand, SVM has achieved 88.60% accuracy using the polynomial kernel with fusion feature. SVM has achieved the lowest accuracy using the local binary patterns (LBP) feature with the polynomial kernel. Bhagya Patil et al. have used SVM to classify three types of plants and achieved 78% accuracy using colour histogram, edge detection, and direction features [11]. HSV color space has been used for feature generation, and SVM has achieved 88.23%, 58.33%, and 66.67% accuracy in trees, shrubs, and herbs classes, respectively. Hang Zhang et al. have used SVM to classify 32 species of plants and achieved 93.8% accuracy using leaf shape and texture [12]. In their research, geometrical features such as aspect ratio, form factor, eccentricity, extent, solidity, and perimeter convexity have been used for shape based features, and from binary images, invariant moments have been calculated. K.B. Shobana et al. has used artificial neural networks (ANN) and SVM to classify plants and achieved 92% and 98% accuracy, respectively [13]. Ana C. Siravenha et al. has used leaf textures to classify 32 plant species using ANN and achieved 91.85% accuracy [14]. Discrete wavelet transform (DWT) and gray-level co-occurrence matrices (GLCM) have been used for describing plant species in their research. Zhaobin Wang et al. has used both shape and textural features of leaf to classify plants, intersection of cortical model (ICM) utilization for extracting textural feature, and center distance sequence (CDS) for obtaining shape feature [15]. Redundant data was been reduced using principal component analysis (PCA) from feature vector, and SVM used as a classifier in their research which achieved 97.82% accuracy. Asem Khmag et al. had achieved 97.69% accuracy using the SVM classifier to recognize leaves based on geometrical and shape features [16]. Mery Paco Ramos et al. used convolutional autoencoder (CAE) and SVM to classify plant leaves and achieved 94.74 % accuracy [17].

No study for poisonous plants identification is being conducted yet. Hence, it is crucial to develop an identification technique for recognizing poisonous plants to reduce the economic loss of the livestock industry caused by livestock poisoning and to ensure the safety of humans, especially children, and pet animals. Hence, an efficient image recognition approach that is based on Xception for poisonous plant recognition is proposed in this paper.

III. Materials and Methods

A. Dataset

As no appropriate dataset of poisonous plants was available, an image dataset of 90000 images has been built for the recognition of poisonous plants. Initially, 18000 images of different poisonous plants leaf were collected, then using different image augmentation techniques PPL dataset has generated. Images of dataset have randomly been divided into training, validation, and test images. Fig. 1 shows 18 representative images belonging to each class of the PPL dataset.

Fig. 1. Sample from the inflammatory dataset: 1) rosary pea 2) sugar apple 3) mexican prickly poppy 4) itchytree 5) giant calotrope 6) hashish 7) colocynth 8) dodder 9) moonflower 10) oleander 11) blue plumbago 12) crepe jasmine 13) philodendron 14) arrowhead 15) dumb canes 16) caladium 17) golden pothos, 18) stinging nettle

PPL dataset contains eighteen classes, where each class contains 3000 training, 1500 validation, and 500 testing images. All images of the PPL dataset contain complex and uniform backgrounds which enable CNN models to learn more efficiently. Image augmentation techniques play a crucial role to overcome the overfitting problem of CNNs during the training phase, five of these techniques have been utilized in this study such as horizontal shift, vertical shift, horizontal flip, 90 degree rotation, and vertical flip. CNNs can learn many irrelevant patterns via image augmentation techniques and under complex conditions, this learning process not only reduces overfitting but also enhances anti-interference ability.

B. State of the art CNN based models

Recently, the use of pre-trained models via transfer learning has become very popular in the field of computer vision. State-of-the-art CNN models can extract a wide variety of features, and these models have been trained with large benchmark datasets. In this study, pre-trained models such as Xception, ResNet152V2, InceptionResNetV2, MobileNetV2, DenseNet201, and NASNetLarge were used via transfer learning for poisonous plants recognition.

Xception is a pre-trained deep learning model which is based on depthwise separable convolution layers and an extreme version of Inception architecture, standard inception modules are replaced with depthwise separable convolutions. The input image size is 299×299 pixels, and the last fully connected layer of Xception architecture has been connected to the Softmax layer with 18 neurons to classify poisonous plants. Xception architecture consists of entry, middle, and exit flow. This architecture contains 36 convolutional layers which are structured into 14 modules. The data first goes into the entry flow, then the middle flow which has been repeated eight times, and then goes through the exit flow. The entry flow phase of Xception is shown in Fig. 2, and the middle and exit flow phases of Xception are shown respectively in Fig. 3.

ResNet152V2 takes 224×224 pixels images as input, and performs batch normalization and ReLU activation at the input. Identity mappings help this architecture to secure the architecture from the vanishing gradient issue, and this architecture has shown excellent performance in accelerating the training process and converging to high accuracy quickly [18]. The last fully connected layer of ResNet152V2 architecture was connected to the Softmax layer with 18 neurons to classify poisonous plants.

The input image size of InceptionResNetV2 is 299×299 pixels, and the architecture of this model has been built with hybrid Inception-ResNet modules [19]. The last fully connected layer of InceptionResNetV2 architecture was connected to the Softmax layer with 18 neurons. In order to, decrease the dimension of the presentation, every hybrid Inception-ResNet module of InceptionResNetV2 is being followed by a reduction module.

MobileNetV2 is basically 53 layers deep pre-trained CNN model that uses inverted residual blocks with bottlenecking features, where the input image size has been used in this study during the training phase for MobileNetV2 is 224×224 pixels [20]. MobileNetV2 is a remarkable enhancement over MobileNetV1. MobileNetV2 is an effective feature extractor and performs very well in segmentation and object detection tasks. To classify poisonous plants, the last fully connected layer of MobileNetV2 architecture was connected to the Softmax layer with 18 neurons. This architecture uses depthwise separable convolution, width multiplier, linear bottlenecks, and shortcut connections.

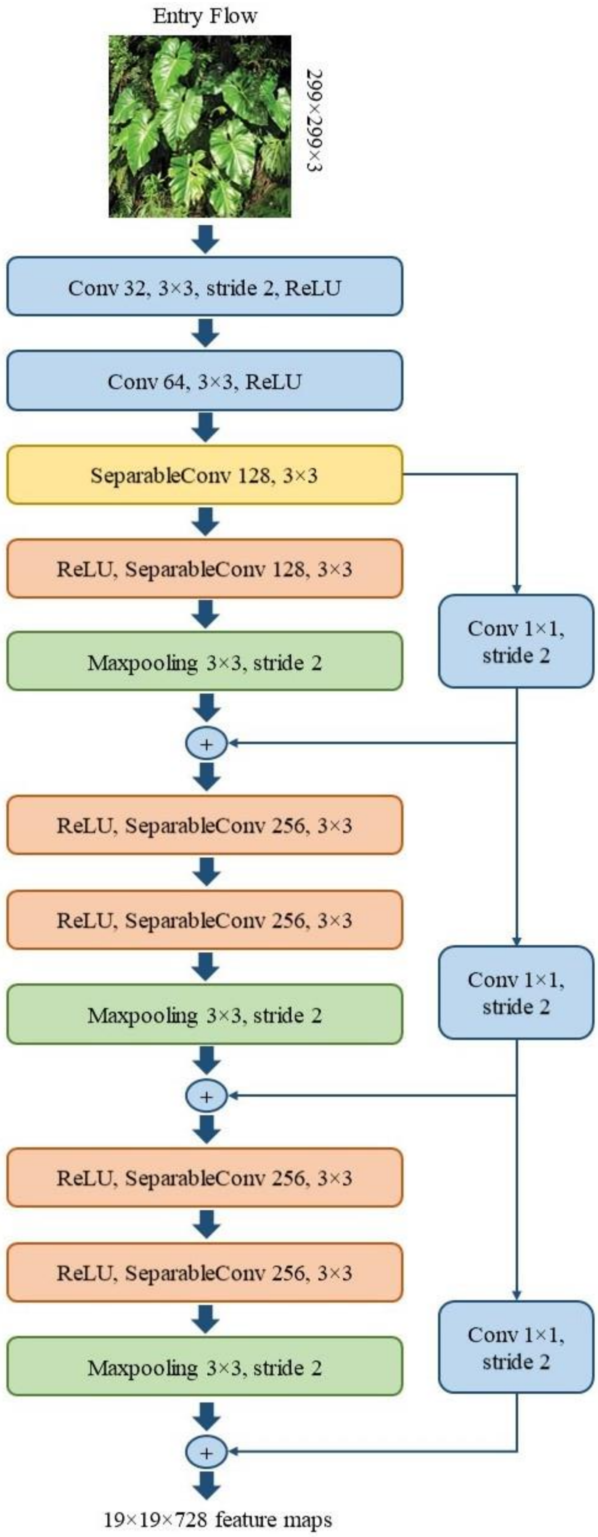

Fig. 2. Entry flow of Xception architecture.

DenseNet201 is basically 201 layers deep pre-trained CNN model of the DenseNet group, where the input image size of the architecture is 224×224 pixels [21]. The last fully connected layer of DenseNet201 architecture was connected to the Softmax layer with 18 neurons. This model is pre-trained on the ImageNet image database, and every layer of

DenseNet201 architecture was connected in a feed-forward manner to each other layer.

NASNetLarge is trained with the ImageNet database, where the input image size of this model is 331×331 pixels [22]. In this study, the last fully connected layer of NASNetLarge architecture was connected to the Softmax layer with 18 neurons. ScheduledDropPath regularization technique of NASNet models remarkably enhances generalization, and this model enables transferability.

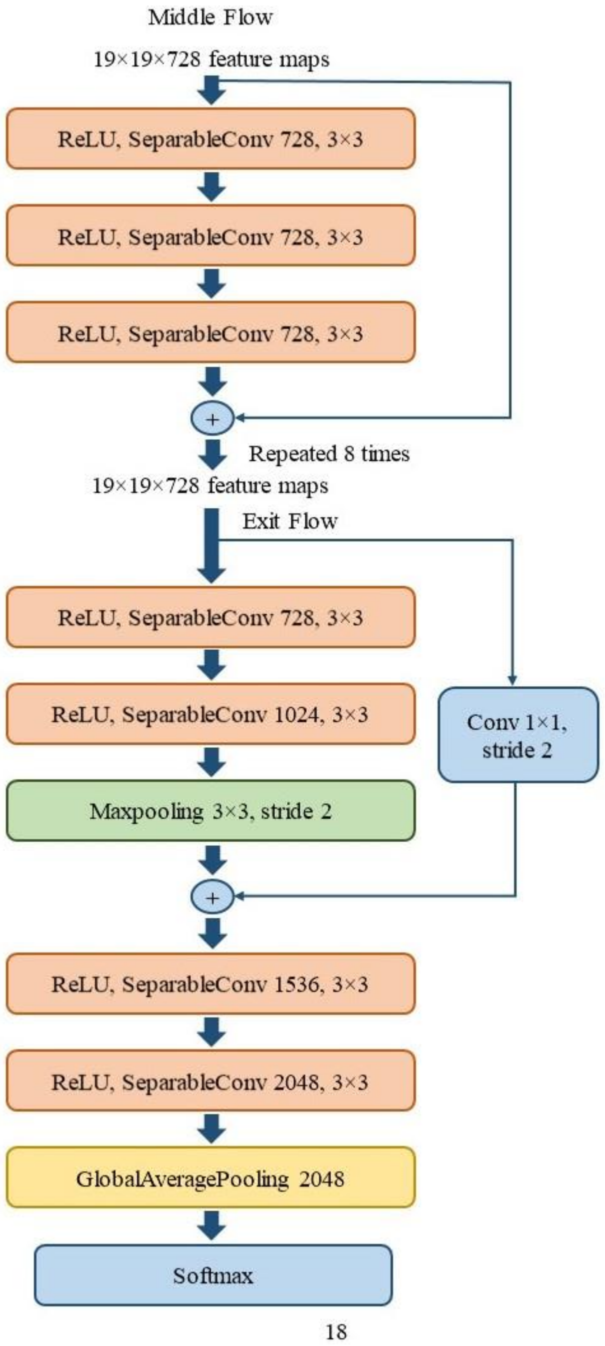

Fig. 3. The middle and exit flow phases of Xception.

IV. Experiments

A. Training

All pre-trained deep learning models have been complied with GPU support in this study. Train and validation set of PPL dataset have been used for training and fitting and test set has been used for evaluating the recognition performance of state-of-the-art CNN models. Existing CNN models used in this study have been fine-tuned to recognize poisonous plants, and in accordance with the problem, the last fully connected layer of all used models has been replaced with 18 outputs. In this study, the resolution of input images was necessarily resized for all models. During the training of pre-trained CNN models, an early stopping technique was used, the number of epochs of MobileNetV2 has is more than others, the number of parameters of NASNetLarge was 84,989,412 which was the highest number of parameters compared to others, and the input size defined for NASNetLarge was also larger than others. Table 1 summarizes the default input size, number of epochs, and number of parameters defined for each pre-trained CNN model.

TABLE I. The default input size, number of epochs, and number of parameters of models

Model Name	Input Size	Number of Epochs	Number of Parameters
Xception	299×299	27	20,898,362
ResNet152V2	224×224	31	58,368,530
InceptionResNetV2	299×299	33	54,364,402
MobileNetV2	224×224	26	2,281,042
DenseNet201	224×224	19	18,356,562
NASNetLarge	331×331	34	84,989,412

B. Performance Metrics

The PPL dataset contains 18 categories of poisonous plant leaf images, so multiclass classification has been utilized in this study. The metrics presented below in (1) to (4) have calculated using indices such as True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) by considering the values in the confusion matrix acquired in such multiclass classifications. Using Sensitivity, Specificity, Accuracy, and Precision, the performance of used state-of-the-art deep learning models were evaluated in this study. Sensitivity (sen) is also known as a true positive rate which measures the ratio of positives that are correctly predicted by the model. On the other hand, Specificity (spe) is known as a true negative rate which measures the ratio of negatives that are correctly predicted by the model. Accuracy (acc) measures the proportion of correct predictions to the total predictions by a model. The precision (pre) represents the accuracy of a model in terms of the number of samples which have been predicted correctly.

For a class p,

$$Sen(p) = \frac{TP(p)}{TP(p) + FN(p)} \tag{1}$$

$$Spe(p) = \frac{TN(p)}{TN(p) + FP(p)} \tag{2}$$

$$Acc(p) = \frac{TP(p) + TN(p)}{TP(p) + TN(p) + FP(p) + FN(p)} \tag{3}$$

$$Pre(p) = \frac{TP(p)}{TP(p) + FP(p)} \tag{4}$$

V. Results and Discussions

The principal purpose of this study is to establish an efficient and rapid recognition approach for recognizing poisonous plants through leaf image classification. The performance of state-of-the-art CNN models such as Xception (M1), ResNet152V2 (M2), InceptionResNetV2 (M3), MobileNetV2 (M4), DenseNet201 (M5), and NASNetLarge (M6) were evaluated in this study with help of several experiments. Xception has shown significant recognition performance compared to other CNN models and achieved 99.71% in training and 99.37% in test accuracy. On the other hand, MobileNetV2 has achieved the lowest training and test accuracy. It has achieved 88.76% test accuracy under the test set of the PPL dataset which contains 9000 images of different poisonous plants leaf. The performance of pre-trained CNN models is presented below in Fig. 4. Finally, Xception is being proposed in this study for poisonous plant recognition, and the confusion matrix of Xception is presented below in Fig. 5.

Fig. 4. Training and Test accuracies of state-of-the-art CNN models.

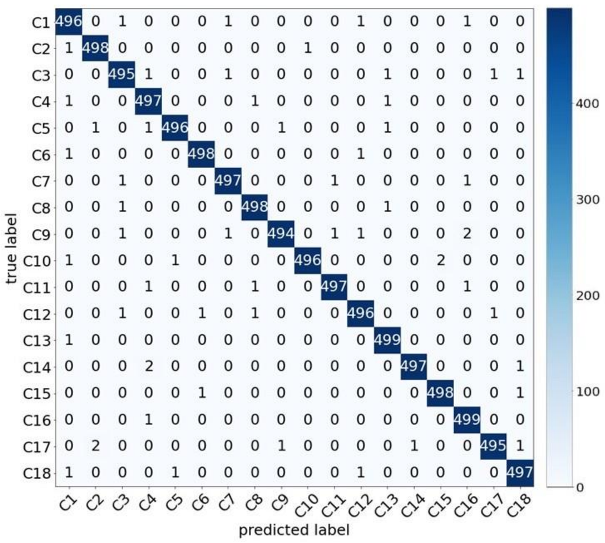

Fig. 5. Confusion matrix of Xception: C1) rosary pea C2) sugar apple C3) mexican prickly poppy C4) itchytree C5) giant calotrope C6) hashish C7) colocynth C8) dodder C9) moonflower C10) oleander C11) blue plumbago C12) crepe jasmine C13) philodendron C14) arrowhead C15) dumb canes C16) caladium C17) golden pothos, C18) stinging nettle

The confusion matrix presented in Fig. 5 represents the efficient recognition performance of Xception architecture in recognizing poisonous plants. Duration of training time has been estimated in this study using time per epoch and number of epochs. MobileNetV2 consumed the lowest training time compared to other CNNs. On the other hand, NASNetLarge consumed the highest training time, and after 34 epochs it reached 96.89% test accuracy. Sensitivity, specificity, precision, and accuracy were used to examine the performance of Xception architecture for each class of the PPL dataset. The sensitivity, specificity, accuracy, and precision value of all classes are presented in Table 2. In the oleander and arrowhead class, Xception obtained the highest sensitivity value, 99.80%, on the other hand, in the rosary pea class Xception acquired the lowest sensitivity value, 98.80%. Xception obtained the highest specificity value in philodendron and caladium class, 99.99%, on the other hand, in the moonflower class Xception obtained the lowest specificity value, 99.93%. According to precision values, Xception has obtained the highest precision in philodendron and caladium class, 99.80%, on the other hand, in the moonflower class Xception obtained the lowest precision, 98.80%. In the hashish, arrowhead, and dumb canes class, Xception achieved the highest accuracy value, 99.96%. Xception has obtained the lowest accuracy value in rosary pea and mexican prickly poppy class, 99.89%.

TABLE II. CLASSIFICATION PERFORMANCE OF XCEPTION FOR EACH CLASS

Class Name	**Sen (%)**	**Spe (%)**	**Pre (%)**	**Acc (%)**
Rosary pea	98.80	99.95	99.20	99.89
Sugar apple	99.40	99.98	99.60	99.94
Mexican prickly poppy	99.00	99.94	99.00	99.89
Itchytree	98.81	99.96	99.40	99.90
Giant calotrope	99.60	99.95	99.20	99.93
Hashish	99.60	99.98	99.60	**99.96**
Colocynth	99.40	99.96	99.40	99.93
Dodder	99.40	99.98	99.60	99.94
Moonflower	99.60	99.93	98.80	99.91
Oleander	**99.80**	99.95	99.20	99.94
Blue plumbago	99.60	99.96	99.40	99.94
Crepe jasmine	99.20	99.95	99.20	99.91
Philodendron	99.20	**99.99**	**99.80**	99.94
Arrowhead	**99.80**	99.96	99.40	**99.96**
Dumb canes	99.60	99.98	99.60	**99.96**
Caladium	99.01	**99.99**	**99.80**	99.93
Golden pothos	99.60	99.94	99.00	99.92
Stinging nettle	99.20	99.96	99.40	99.92

In order to more perceptibly demonstrate the class-wise performance of Xception architecture discussed in this study, the false prediction numbers of each class has been calculated. False prediction number represents the number of incorrectly classified images of each class by CNNs. Xception misclassified one image in philodendron and caladium class, on the other hand, in moonflower class, it wrongly predicated six images. The false prediction numbers of Xception on the test set of the PPL dataset for each class is presented below in Fig. 6.

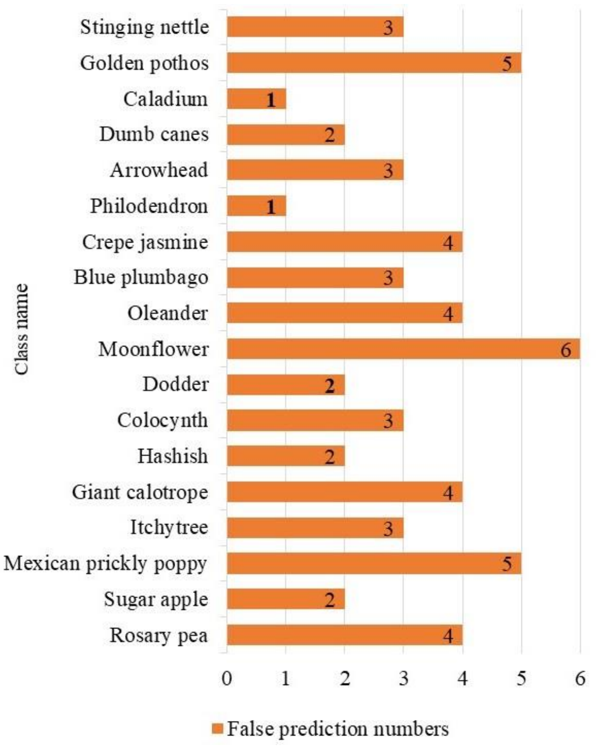

Fig. 6. False prediction numbers of Xception for each class.

An experimental study was conducted to analyze the recognition time of state-of-the-art CNN models. A new test dataset has been created which contains 18 leaf images of the different poisonous plants, and these images were not in the PPL dataset. In this experiment, Xception has classified all images correctly with 10.2 seconds, and MobileNetV2 has shown less recognition performance than others that misclassified four images and consumed 20.9 seconds. The performance of NASNetLarge architecture was very close to Xception, misclassified one image, and consumed 14.7 seconds. InceptionResNetV2 has misclassified three images and consumed 16.1 seconds. The result obtained from several experimental studies demonstrates that the proposed Xception model can efficiently recognize poisonous plants with less time compared to other CNN models. The accuracy and loss curve of both training and validation of Xception architecture is given below in Fig. 7 and Fig. 8.

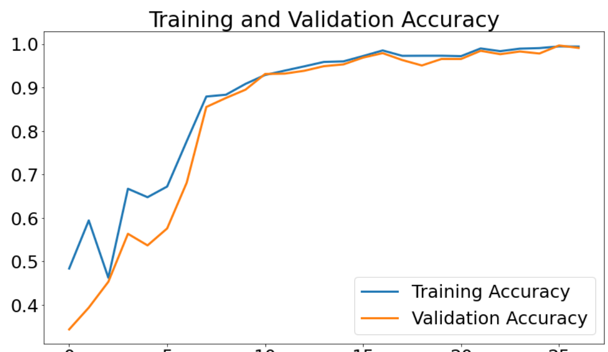

Fig. 7. Training and validation accuracy curve of Xception.

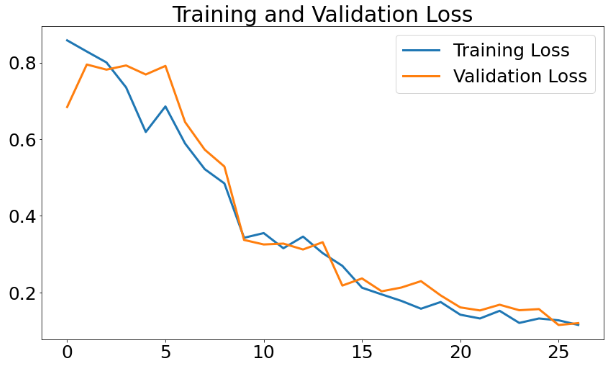

Fig. 8. Training and validation loss curve of Xception.

The outcome of this study was compared with several studies that were introduced in the literature for recognizing various types of plants, presented below in Table 3, and this study is the first attempt to recognize poisonous plants using deep learning techniques.

TABLE III. COMPARISON OF DEEP LEARNING METHODS FOR FOOD RECOGNITION.

Study	**Method**	**Number of Classes**	**Accuracy**
Hulya Yalcin et al. [10]	CNN	16	97.47%
Bhagya Patil et al. [11]	SVM	3	78.00%
Hang Zhang et al. [12]	SVM	32	93.80%
K.B. Shobana et al. [13]	SVM	2	98.00%
Ana C. Siravenha et al. [14]	ANN	32	91.85%
Zhaobin Wang et al. [15]	SVM	12	97.82%
Our study	Xception	18	**99.37%**

VI. CONCLUSION

Recently, transfer learning approaches have become very popular in developing computer vision based approaches for expeditious recognition. This paper has introduced a computer vision approach for the recognition of eighteen poisonous plants by classifying leaf images using state-of-the-art CNN models such as Xception, ResNet152V2, InceptionResNetV2, MobileNetV2, DenseNet201, and NASNetLarge via transfer learning. Based on 18000 collected images of different poisonous plants leaf, the PPL dataset of 90000 images was generated using five image augmentation techniques. To evaluate the performances of CNNs, the test set of 9000 images of the PPL dataset was used. According to several experiment results, Xception has shown significant performance in this study compared to others and achieved 99.71% training and 99.37% test accuracy. MobileNetV2 has consumed less training time than other CNNs and achieved 88.76% test accuracy. NASNetLarge has achieved 96.89% test accuracy but consumed the highest training time. The outcome of this study validates that the proposed Xception architecture realizes end-to-end recognition of poisonous plant leaf.

In future work, it is planned to reduce the computation, apply other pre-trained deep learning architectures and establish a large dataset of poisonous plants leaf by increasing the number of classes and images.

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