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CFNN for Identifying Poisonous Plants

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Abstract

Identification of poisonous plants is a hard challenge for researchers because of the great similarity between poisonous and non- poisonous plants. Traditional methods to identify poisonous plant can be tiresome, therefore, automated poisonous plants identification system is needed. In this work, cascade forward neural network framework is proposed to identify poisonous plants based on their leaves. The proposed system was evaluated on both (poisonous leaves/non-poisonous leaves) which are collected using smart phone and internet. Combination of shape features and statistical features are extracted from leaf then fed to cascade-forward neural network which used TRAINLM function for training. 500 samples of leaf images are used, 250 samples are poisonous, the remaining 250 samples are non-poisonous.300 samples used in training, 200 samples for testing. Our system is achieved an accuracy value of 99.5%.

Keywords: Cascade Forward Neural Network (CFNN), First Order Statistical Features, Poisonous Plants, Shape Features, TRAINLM Function

Introduction

Poisonous plants can define as plants that contain poisonous substances that cause death when touched or ingested. Poisonous plants cause heavy losses to livestock and the economy in all countries of the world, it is seriously dangerous to animals and humans, for example stinging nettle causes skin irritation as well as it is very toxic for animals [1]. The human used plants mainly for food and to cure diseases, he learns over time how to differentiate between beneficial and harmful plants in order to use it as food, drinks, medicine, condiment and perfume [2]. Farmers annoyed because their livestock dies immediately after eating poisonous plants. The primary reason of cattle poisoning is lack of experience of farmers to recognize and detect harm plants also poisonous plants are look similar to the non-poisonous one, that can lead to many accidents caused by discrimination errors [3]. Farmers can detect poisonous plants in two ways: farmers in agricultural fields have to travel several miles to meet an agricultural expert, which is expensive and tiring or they can use their eyes to diagnose poisonous plants, which is tiresome and time-consuming process, so automated poisonous plants identification system is necessary. Neural network technique is the most common and useful machine learning mechanism which aims to build algorithms capable of making machines learn automatically without human involvement. There are two main phases in neural networks; training and testing, the training phase complexity depends on the topology of the network, thus number of hidden neurons must be specified precisely [4]. In this work cascade forward neural network is used which is a kind of neural network offers a connection between the input layer and each previous layer, all the input layers have been trained one by one in a short time and acceptable cost. This work aims to identify plants whether it is poisonous or non-poisonous. In this framework, leaves of plants is collected with suitable pre-processing processes preparing it for the next phase. In the second phase, hybrid features are extracted (shape features, statistical features) from the input leaf image. In the last phase, cascade forward neural network is used.

This paper has been organized as follows: Section 2 reviews the related works. In section 3 methods and materials used in this work are explained. In section 4 experimental results are presented. Section 5 discusses the conclusions and future works.

Literatures Review

Many recent studies concentrate on plants poisonous identification: In [1] eighteen types of poisonous plants were recognized, image augmentation techniques were used to generate dataset which divided into three sets of images; the first set contained 54000 which used for training, the second set contained 27000 images which used for validation, the last set contained 9000 images which used for testing. (6) different models of deep learning was used in order to classify poisonous plants such as: NASNetLarge which was trained with ImageNet database using image of size 331*331, ResNet152V2 which was trained using image of size 224*224, Xception which has 36 convolutional layers and was trained using image of size 299*299, MobileNetV2 which has 53 layers and was trained using image of size 224*224, InceptionResNetV2 which was trained using image of size 299*299, and DenseNet201 which has 201 layers was trained using image of size 224*224. The last layer of all models was connected with eighteen neurons to the Softmax layer. The authors used four performance parameters to evaluated their study: specificity, precision, sensitivity and accuracy. Xception has achieved high performance 99.37%.

Authors in [3] identified three kinds of poisonous herbs which were difficult to recognize by eye based on deep learning models. Three models were used: VGGNet16 which was trained using 31 epochs, ResNet50 which was trained using 36 epochs, and MobileNet which was trained using 52 epochs, 500 samples of herbs were obtained using smartphones and 100 samples were obtained from the internet, images were preprocessed by using Conquer-Evaluation-Divide algorithm that removed edges which were inaccurately detected. Two techniques were used to increase models' accuracy. The first was edges extraction using canny filter and the second was using transfer learning. Three models of deep learning were used; ResNet50, MobileNet, and VGGNet16. MobileNet-TL has achieved high accuracy than other models, it achieved 99.4% of accuracy in recognize three species of herbs.

Mushroom in [5] were classified to poisonous or not poisonous based on multi-layer artificial neural network model, the structure of their model was: 22 input neurons, three of hidden layer, one output neuron. The mushroom dataset was collected from California university center for machine learning and intelligent systems, 8124 samples were used, 5724 samples for training, 2400 samples for testing, 22 features (shape, color) were extracted then fed into JNN (just neural network) which was trained for 161501 epochs, number of hidden layers were tested and the best accuracy was 99.25% when used three hidden layers. Another work was identified five types of mushroom: Kancing, Merang, Kuping, Tiram Merah and Lingzhi Kerang whether it edible or inedible, 30 images were collected, 15 images for training data and 15 images for test data. The images were converted to a grayscale image, first order statistics features were extracted then fed to ANN with backpropagation algorithm, number of hidden layers were tested 5, 10, 15, 20, the best accuracy was 93% on neuron 20 [6].

The goal of the proposed work was to address the issues which lack addressing in order to construct a reliable and efficient system for identifying poisonous plants.

The contribution of this work is epitomized as follows:

1- Leaf image is processed in order to create appropriate training data. The intricacy of the image and the over fitting during training phase can be ascribed to image contrast.
2- Good number of images are used which were selected from several categories and collected under different circumstances to ensure the diversity of the database.
3- The suggested system will allow identification of preferential features in leaf images, it can also deal with every leaf image which collected under various circumstances regardless of their shape, size and color.

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The Proposed Framework Materials and Methods

This work aims to identify poisonous plants based on their leaves, the presented work includes three phases; pre-processing phase which is used to prepare input images for the next phase; in the 2nd phase combination of shape and statistical features are extracted; at the last phase the cascade-forward neural network is used to classify plants into poisonous/non-poisonous, Fig.1 illustrates the presented framework.

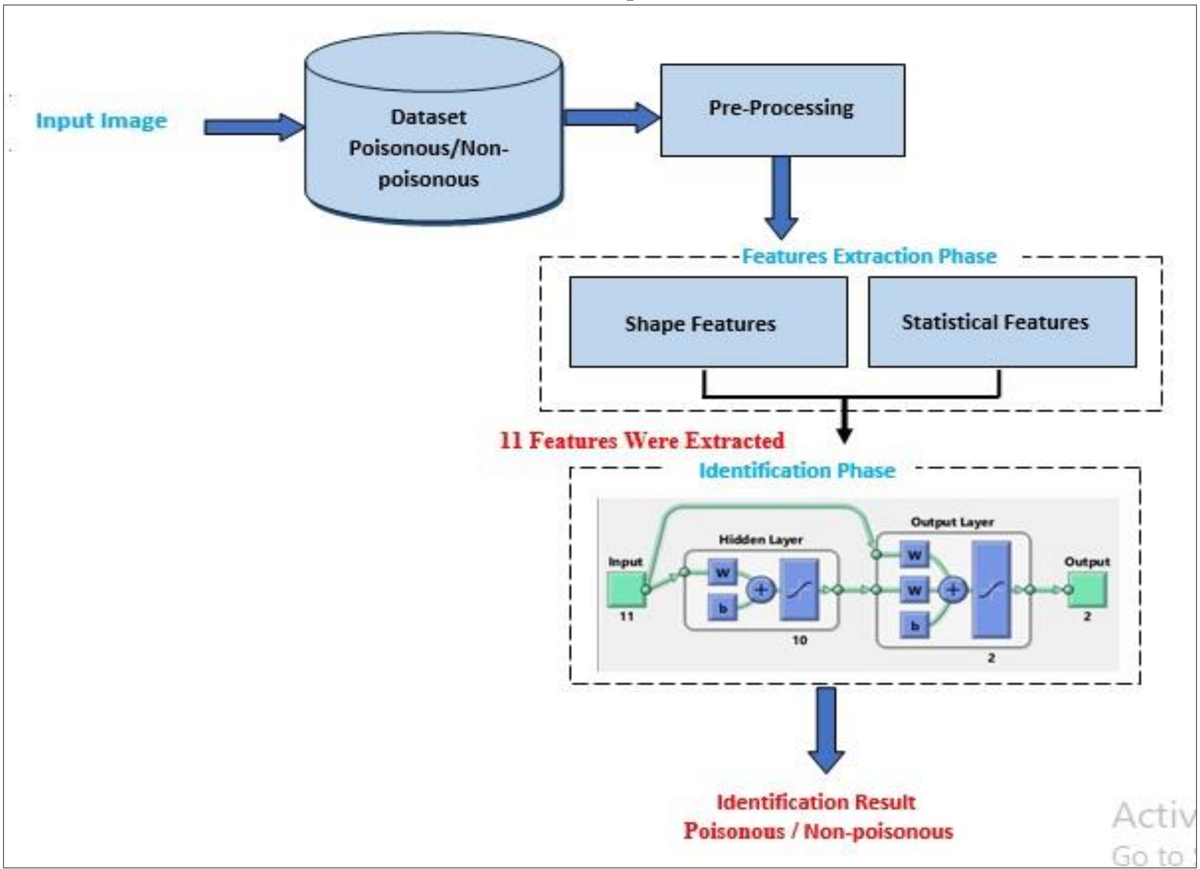

Figure 1. The Presented PPICFNN Framework Diagram

Image Acquisition and Pre-processing

Images of poisonous /non- poisonous leaves were collected using internet and smartphone, 500 images were used which have different shape, size, color then all images were resized into size 256×256. 20 species of plants were used, 25 samples for each species. 300 of our samples were used in training, the rest were used in testing. Number of pre-processing processes were performed on leaves [7] in order to prepare images for the next phase.

Features Extraction

Features extraction phase aims to extract robust and relevant characteristics from image, features can be classified into: statistical features, shape features, color features and texture features [8]. In this phase combination of shape and statistical features are extracted, (11) relevant and robust features are extracted from leaf image: (4) were the first order statistics features and (7) features were extracted from the shape of leaf image.

Statistical Features

The statistical features are used to quantify characteristics of an object area by utilizing the gray level distribution space relationship of an object. Variant first order statistical features are extracted, it based on the individuality of pixel values to describe the region of image. To obtain statistical characteristics, first order histogram was used, these characteristics give an excellent indication of intensity distribution. Four first order statistics

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features are extracted: mean, standard deviation, kurtosis and the skewness [9], Eqs. 1, 2, 3 and 4 are clarifying each of these features [10].

$$M= \frac{1}{n} * \Sigma x \Sigma y\ I(x,y) \quad \ldots\ldots\ 1$$

$$Stdv= \sqrt{\frac{\Sigma x \Sigma y (I(x,y)-IM)^2}{n}} \quad \ldots\ldots\ 2$$

$$Ske= \frac{1}{n} * \sqrt{\frac{\Sigma x \Sigma y (I(x,y)-IM)^3}{Stdv^3}} \quad \ldots\ldots\ 3$$

$$Kut= \frac{1}{n} * \sqrt{\frac{\Sigma x \Sigma y (I(x,y)-IM)^4}{Stdv^4}} \quad \ldots\ldots\ 4$$

Where:
M: symbolize the mean.
Stdv: symbolize the standard deviation.
Ske: symbolize the skewness.
Kut: symbolize the kurtosis.
I(x,y): symbolize the intensities of image.
n: symbolize the number of pixels in image.

Shape Features

Shape is a paramount visible feature; it considers one of the major features used to depict the content of image. Shape description methods can be classified into two types: methods based on contour of object and methods based on region of object, both are divided into structural and global. Seven of shape features are extracted from leaf image: area, perimeter, circularity ratio, wavelet energy, solidity, convex area and eccentricity [11].

Cascade-Forward Neural Network of The Presented Framework

Neural networks (NN) are exceedingly accepted as a technique offering a way to solve complex problems due to their robust ability of non-linear mapping. neural networks are selected because it is extremely used in classification, its usefulness in machine learning [12].

In this work, cascade forward neural network is used which is similar to feed-forward networks but CFNNs has a direct weighted connection from the input to the output layer. In CFNNs the input is connected to all hidden layers behind. This configuration can give more flexibility in the learning process, thereby enhancing the ability of mapping [13]. The complexity of the training stage is directly proportional to the change in CFNN structure. CFNN has powerful learning and popularization capabilities than FFNN, but because of the high structure complexity comparatively long time for training process is demanded [14]. Eq. 5 bellow formed CFNN model [15]:

$$y=\sum_{k=1}^{m} F^k w_k^k x_k + F^o \left(\sum_{j=1}^{L} w_j^o\ F_j^h\left(\sum_{k=1}^{m} w_{jk}^h\ x_k\right)\right) \quad \ldots\ldots\ 5$$

Where:

F^k: symbolize the activation function.
x_k: symbolize the input samples.
w_k^k : symbolize the weights.
F^o: symbolize the activation function of output layer.
F_j^h: symbolize the activation function of the hidden layer.

Then the bias is added to the input layer and the activation function of each node in the hidden layer as shown in Eq. 6, the structure of CFNN is shown in Fig. 2.

$$Y=\sum_{k=1}^{m} F^k w_k^k x_k + F^o \left(w^b + \sum_{j=1}^{L} w_j^o\ F_j^h\left(w_j^b + \sum_{k=1}^{m} w_{jk}^h\ x_k\right)\right) \quad \ldots\ldots\ldots\ 6$$

Where:
w^b: symbolize the bias.

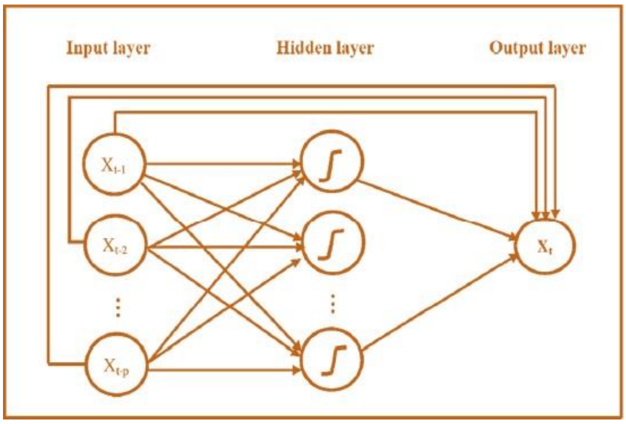

Figure 2. Structure of CFNNs with More Layers [16].

Training/Testing Phase

CFNN model is created then training using TRAINLM function which is the best and the fastest than others. The number of hidden layers and neurons depend on the number of input samples and the number of outputs. The performance of CFNN is

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measured using measures square error which is a perfect estimator that measures the average of the squares of the errors for numerical predictions [16].

Poisonous-Inputs matrix and Poisonous-Targets matrix; symbolize the Input and Target layers for the CFNN, the Poisonous-Inputs matrix symbolizes the significant features extracted from the leaf images, (11) hybrid features values were extracted from each leaf. 500 leaf images dataset was acquired, 250 leaf images for poisonous plants, 250 leaf images for non-poisonous plants. The output was two outputs which represent poisonous or not poisonous plant, binary representation is use [1 0]; [0 1]. The image dataset was organized as: 60% of images for training; 40% for validation and testing.

The execution results of CFNN can be shown in Fig.3; Table. 1. bellow shows the default parameters of target matrix encoding.

Table 1. The default parameters of target matrix encoding.

Type of plants	Encoding for target matrix
Non-Poisonous plant	10
Poisonous plant	01

Table. 2: bellow shows the performance of training and testing stage.

Table 2. The performance of testing stage.

Number of hidden neurons	Testing Accuracy	Performance	Best Validation	Epoch iteration
6	88.9%	0.243	0.033395 at epoch 25	31
8	91.7%	0.879	5.577e-05 at epoch 52	59
10	99.5%	0.445	0.010828 at epoch 11	17
12	88.9%	0.374	0.097271 at epoch 33	35
14	88.9%	0.394	0.24124 at epoch 15	21
16	77.8%	0.227	0.16664 at epoch 12	18

Different number of hidden neurons were tried in this work as explained in Table. 2. The results showed that this framework achieved great results, the best validation 0.010828 at epoch 11 with 17 iterations.

Results and Discussion

This framework is implemented using processor Intel (R) Core (TM) i5-2430M CPU @ 2.40GHz, RAM 4gb, x64 based processor, R2020a matlab software and Windows 10. (500) colored leaf images (poisonous and non-poisonous) are used as leaf database. Colored leaf images are obtained using smart phone and internet. In this work CFNN are used with 11 neurons for input layers, 10 for the hidden layers and 2 for the output layers as shown in Fig.3.

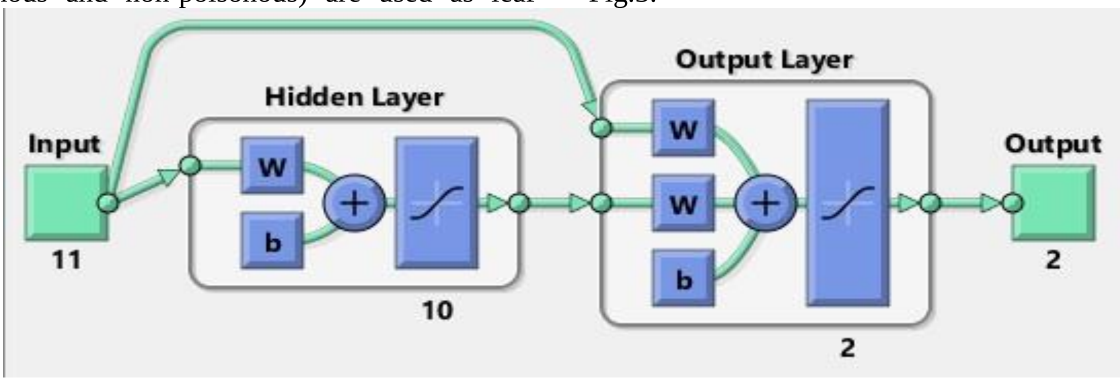

Figure 3. The Architecture of the Presented Work Cascade-Forward Neural Network

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Levenberg-Marquardt optimization is used to adjust the adaptation in bias and weight values, MES is used to measure the errors. 300 images were used for training the system then 200 images were used to evaluate the identification accuracy of the system. Number of hidden layers are affected the accuracy, different number of hidden layers are selected for testing: 6,8,10,12,14 and16, the accuracy rate is determined as illustrated in Fig.4, the best number of hidden layers is ten layers.

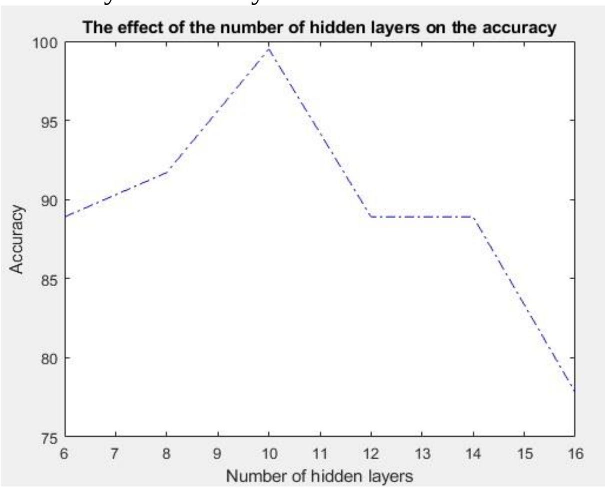

Figure 4. The Effect of the Number of Hidden Layers on the Accuracy.

At each run there were number of the epochs, the best number of the epochs that achieves the best accuracy, Fig.5, illustrated the accuracy for various number of epochs.

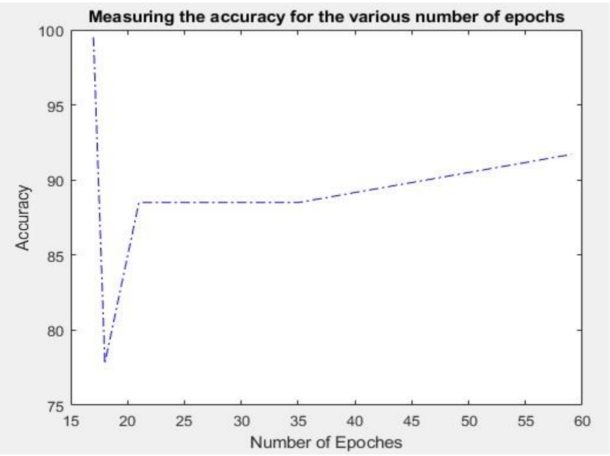

Figure 5. The Accuracy for Various Number of Epochs.

This framework is achieved 99.5% of testing accuracy, Fig. 6. bellow illustrated the best performance of the presented work.

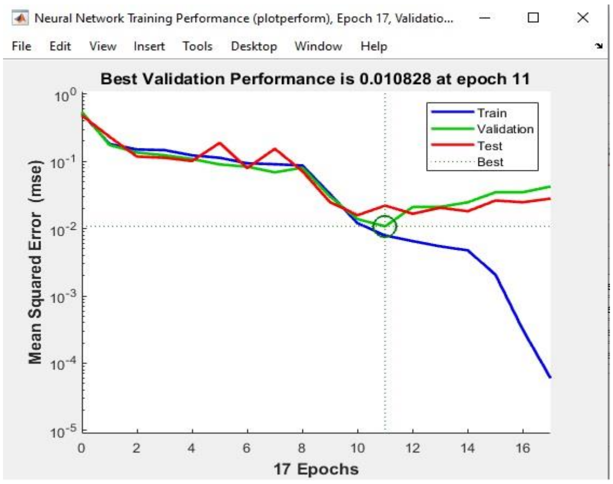

Figure 6. The Best Performance of the Presented Work, Best Validation=0.010828 at Epoch 11.

Our proposed work is evaluated based on four methods: accuracy, specificity, recall and F1-score as illustrated in Fiq.7.

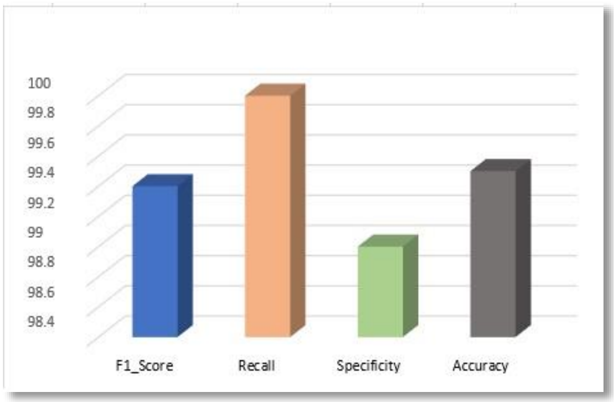

Figure 7. The Proposed Work Evaluation Based on Four Performance Measures.

The results of this work were compared with previous studies, Table. 3. bellow shows more details:

Table 3. Comparison of our work with previous works.

Ref.	Method	Number of Species	Accuracy
Hridoy et al.[1]	Deep learning using model Xception	18	99.37%
Cho et al. [3]	Deep learning using model MobileNet-TL	3	99.4%
Alkronz et al. [5]	Multi-Layer artificial neural network model	2	99.25%
Fadlil et al. [6]	ANN with backpropagation algorithm	2	93%
The presented work	Cascade-forward neural network.	20	99.5%

Fig.8, shows the comparison of our work with previous works.

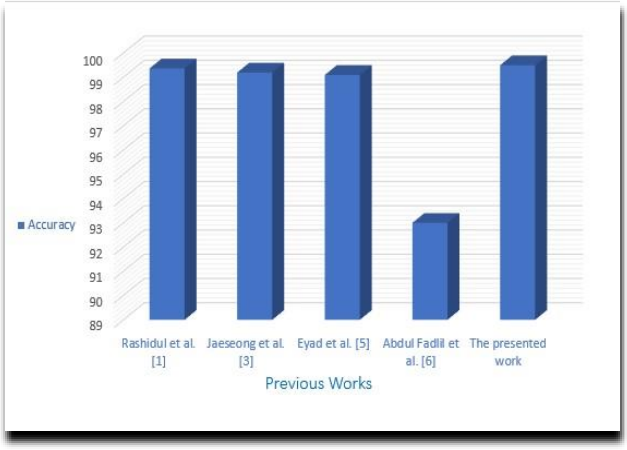

Figure 8. Comparison Our Work with Previous Works.

Conclusion

Early identification of poisonous plants will reduce losses that can occur in livestock and agricultural crops. Plants are difficult to recognized whether it is poisonous/non-poisonous because it seems similar in shape, color, size and this is a challenge, it seems very important to have a demonstrated system for identifying poisonous plants instantaneously. In this work, CFNN framework with TRAINLM training function is proposed for poisonous plants identification. The proposed work contains three stages: pre-processing stage, features extraction stage and identification stage. Hybrid features (shape, statistical) were extracted then fed to cascade forward neural networks. 500 leaf images were obtained, 60% of them for training phase and the rest 40% for validation and testing. The reliability in this work is its capability to identify poisonous plants accurately. The proposed identification framework is achieved 99.5% of testing accuracy, our work accuracy outperforms other previous works as explained in Table. 3. In future work, we are planned to increase our dataset, identification poisonous plants based on other parts of the plant, such as flowers and using another learning algorithm.

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Author’s Declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images that are not ours have been included with the necessary permission for re-publication, which is attached to the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee in department of Environmental Engineering, University of Mustansiriyah.

Author's Contribution Statement

This work was carried out in collaboration between all authors. I M H presented the idea, carried out the experiments, wrote the manuscript. S A H, collected samples, provided useful information about CFNN.

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الشبكة العصبية المتتالية لتحديد النباتات السامة

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الخلاصة

يعتبر التعرف على النباتات السامة تحديًا صعبًا للباحثين بسبب التشابه الكبير بين النباتات السامة وغير السامة. يمكن أن تكون الطرق التقليدية لتحديد النباتات السامة مرهقة، لذلك يلزم وجود نظام آلي لتحديد النباتات السامة. في هذا العمل، تم اقتراح إطار عمل الشبكة العصبية المتتالية لتحديد النباتات السامة بالاعتماد على أوراقها. تم تقييم النظام المقترح على كل من (الأوراق السامة / غير السامة) التي تم جمعها باستخدام الهاتف الذكي والإنترنت. يتم استخراج مزيج من ميزات الشكل والميزات الإحصائية من الورقة ثم تغذيتها إلى الشبكة العصبية المتتالية التي تستخدم دالة TRAINLM للتدريب. تم استخدام 500 عينة من صور الأوراق، 250 عينة سامة، و250 المتبقية غير سامة، و300 عينة مستخدمة في التدريب، و200 عينة للاختبار. نظامنا حقق دقة تصل إلى 99.5٪.

الكلمات المفتاحية : الشبكة العصبية المتتالية، الميزات الإحصائية من الدرجة الأولى، النباتات السامة، ميزات الشكل، دالة TRAINLM.