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Abstract Potato leaf blight is one of the most devastating global plant diseases because it affects the productivity and quality of potato crops and adversely affects both individual farmers and the agricultural industry. Advances in the early classification and detection of crop blight using artificial intelligence technologies have increased the opportunity to enhance and expand plant protection. This paper presents an architecture proposed for potato leaf blight classification. This architecture depends on deep convolutional neural network. The training dataset of potato leaves contains three categories: healthy leaves, early blight leaves, and late blight leaves. The proposed architecture depends on 14 layers, including two main convolutional layers for feature extraction with different convolution window sizes followed by two fully connected layers for classification. In this paper, augmentation processes were applied to increase the number of dataset images from 1,722 to 9,822 images, which led to a significant improvement in the overall testing accuracy. The proposed architecture achieved an overall mean testing accuracy of 98%. More than 6 performance metrics were applied in this research to ensure the accuracy and validity of the presented results. The testing accuracy of the proposed approach was compared with that of related works, and the proposed architecture achieved improved accuracy compared to the related works.

Keywords Potato leaf blight · Classification · Deep convolutional neural network

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1 Introduction

Current agricultural practices are incredibly challenging. The agricultural sector has matured into an extremely competitive and international industry in which farmers and other actors must deliberate local climatic and environmental aspects as well as world-wide ecological and political factors to ensure their economic subsistence and sustainable production [1–3].

Potato is considered to be an efficient crop because it produces more protein, dry matter and minerals per unit area compared to cereals. However, potato production is vulnerable by numerous diseases, leading to yield losses and/or a decreasing in tuber quality and causing a rise in potato price. Many diseases especially parasitic diseases affect potato crops, leading to large crop yield reductions and significant economic losses for farmers and producers [4] Traditional methods such as visual inspections, are commonly used to detect and diagnose plant diseases. However, these methods have several disadvantages; they are expensive because they require continual monitoring by experts and time consuming because experts are not always available locally [5, 6].

Recent advances in artificial intelligence have highlighted and accelerated agriculture using various types of Artificial Intelligence essential technologies, such as mobile devices, independent agents (devices) operating in unrestrained environments, independent and collaborative scenarios, robotics, sensing, computer vision, and interactions with the environment. Integrating multiple partners and their heterogeneous information sources has led to the application of semantic technologies [7, 8]. The continuous interest in creating reliable predictions for planning purposes and for controlling agricultural activities requires interdisciplinary cooperation with field specialists for example, between the agricultural research and artificial intelligence domains [7].

Many studies have investigated the problem of classifying plant leaf diseases using computer algorithms. These trials have included different leaf types, including apple, peach, grapevine, cherry, orange, cotton and others [9–11]. In [9], authors proposed an architecture for to detect leaf diseases by converting images from RGB to HSV domain to detect the diseases spots in leaves. In [10], another model was introduced to detect cotton diseased leaf using particle swarm optimization (PSO) [12] algorithm and feed forward neural network and it achieved testing accuracy 95%. In [11], more than 4483 images for different leaves types of fruits which included pear, cherry, peach, apple, and grapevine leaves have been used in a deep learning architecture to classify the images into 13 different classes and achieved accuracy from 91% and 98%.

The focus of this research is potato leaf blight classification; this problem was also addressed in [13, 14]. In [13], the presented algorithms extracted more than 24 (colour, texture, and area) features. The texture features were extracted from the grey level co-occurrence matrix, and a backpropagation neural network-based classifier was used to recognize and classify unknown leaves as either healthy or diseased. The model achieved an overall testing accuracy of 92%.

In [14], the proposed system involved three main phases: segmentation, feature extraction, and classification. Image segmentation was conducted using the k-means algorithm. Then, three types of features were extracted from the segmented images: colour, texture, and shape. Finally, the extracted features were input into a feed-forward neural network for classification. The overall testing accuracy was 95.30%.

The main contributions of this research are a proposed deep neural network architecture with data augmentation which led to a significant improvement in testing accuracy 98% for potato leaf blight classification. Moreover, the proposed achieved a competitive result if the is compared to related works. The rest of this paper is organized as follows. Section 2 introduces artificial intelligence and deep learning. Section 3 describes the dataset. Section 4 presents the proposed CNN architecture, and Sect. 5 introduces the augmentation techniques. The experimental results and environment are reported in Sect. 6. Finally, Sect. 7 summarizes the main findings of this paper.

2 Artificial Intelligence and Deep Learning

In 1947, Alan Turing foreseen that intelligent computers might ascend by the end of the century, and in his classic 1950 article "Can a machine think?" he proposed a test for evaluating whether a machine is intelligent. At the beginning of the 1960s, neural network research became widespread in the world's most prominent laboratories and universities [15]. After that year, AI field has been boosted for the next 50 years in research and industry [16–18].

Artificial intelligence is a broad field that includes both machine learning and deep learning, as illustrated in Fig. 1. Machine learning is a subdomain of artificial intelligence, and deep learning is a subdomain of machine learning [19].

2.1 Deep Learning Activation Functions

Activation functions comprise the non-linear layers and are mixed with other layers to accomplish a non-linear transformation from input to output [20]. Therefore, better feature extraction can be reached by choosing appropriate activation functions [21, 22]. The choice of activation function is critical for complex real-world information such as text, image, and video to make neural network learn in adequate matter. If a linear activation function was selected to learn from images will lead to losing important features as linear functions are only single-grade polynomials, while non-linear functions is the common presentation for features for images because of they are multi-grade polynomials and multi-layered deep neural networks can learn meaningful features from data [23]. There are several common activation functions, denoted by f. Here are some examples:

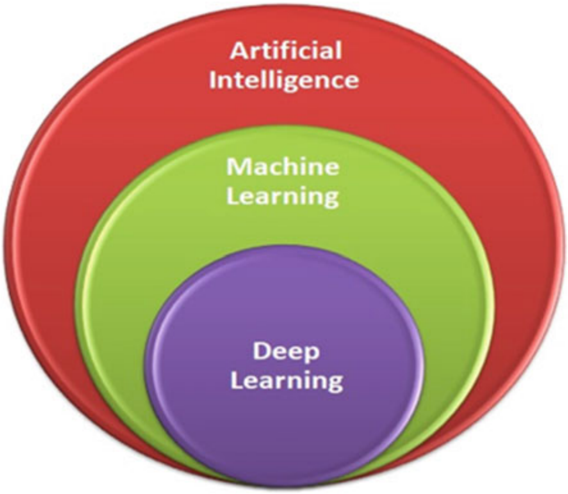

Fig. 1 Artificial intelligence, machine learning, and deep learning

- **Sigmoid function:** Changes variables to values fluctuating from 0 to 1 as shown in Eq. (1) and is frequently used as a Bernoulli distribution [24]:

$$f(a) = \frac{1}{1 + e^{-a}}, \tag{1}$$

where a is the input from the front layer. An example of the Bernoulli distribution is shown below:

$$\tilde{f} = \begin{cases} 0 \text{ if } f(a) \le 0.5 \\ 1 \text{ if } f(a) > 0.5 \end{cases}. \tag{2}$$

- **Hyperbolic tangent:** As shown in Eq. (3), the derivative of f is calculated as $f' = 1 - f^2$, to be applied into back propagation algorithms:

$$f(a) = \tan \mathrm{h}(a) = \frac{e^a - e^{-a}}{e^a + e^{-a}}. \tag{3}$$

- **Softmax:** SoftMax is the most frequent layer and is used in the last fully connected layer and calculated as follows:

$$f(a) = \frac{e^{a_i}}{\sum_j e^{a_j}} \tag{4}$$

- **Rectified linear unit (ReLU)**: As shown in Eq. (5), the variants of this function and it is original one show superior performance in many situations; thus, ReLU is currently the most widespread activation function in deep learning [25–27].

$$f(a) = \max(0, a). \tag{5}$$

Softplus: As shown in Eq. (6), Softplus is one of the ReLU variants that represents a smooth estimate of ReLU.

$$f(a) = \log\left(1 + e^{a}\right). \tag{6}$$

2.2 *Neural Networks*

Deep learning architectures depends on Feed-forward neural network architectures. These architectures consist of multiple layers. In these architectures, the neurons in one layer are linked to all the neurons in the succeeding layer. The hidden layers are between the input layers and output ones [28].

In most artificial neural networks, Artificial neurons are represented by mathematical equations that model biological neural structures [29]. Let $x = (x_1, x_2, x_3 \ldots, x_n)$ be an input vector for a given neuron, $w = (w_1, w_2, w_3 \ldots, w_n)$ be a weight vector, and b be the bias. The output of the neuron is presented in Eq. (7):

$$Y = \sigma(w.x + b), \tag{7}$$

where σ represents one of the activation functions presented in the previous section.

2.3 *Convolutional Neural Network*

The convolutional neural networks (CNN) are deep artificial neural networks that have been applied to image classification and clustering, and object identification within images and video scenes. More specifically, they have also been used to categorize tumours, faces, individuals, street signs and many other types visual data. Recently, CNNs have become popular in computer vision fields, and medical image analysis and applications mainly depend on CNNs.

CNNs do not perceive images as humans do. Their main components typically consist of convolutional layers and pooling layers in its first stages [30]. The layers in a CNN are trained in a robust manner.

Convolutional Neural Networks are the most successful type of architecture for image classification and detection to date. A single CNN architecture contains many different layers of neural networks that work on classifying edges and simple/complex features on shallower layers and more complex deep features in deeper layers. An image is convolved with filters (kernels) and then pooling is applied, this process may go on for some layers and at last recognizable feature are obtained [31]; however, the same combination of filters is shared among all neurons within a feature map. Mathematically, the sum of the convolutions is used instead of the dot product in Eq. (8). Thus, the k-th feature map is calculated by

$$y^k = \sigma\left(\sum_m w_m^k * x_m + b^k\right), \tag{8}$$

where the set of input feature maps are summed, * is the convolution operator, and w_m^k represents the filters.

A pooling layer works on reduce the spatial dimensions of the representation output by a convolutional layer; this operation reduces the number of parameters and the amount of computation within the network. Pooling works self-sufficiently on its input at every depth and has a stride parameter similar to that of a filter in a convolutional layer. Max pooling is most commonly applied.

3 Potato Leaf Blight Dataset

The potato leaf blight dataset was introduced in the Kaggle competition in 2016 [32]. The dataset consists of 1,722 images classified into three categories: healthy potato leaves (122 images), early blight potato leaves (800 images) and late blight potato leaves (800 images). Figure 2 provides some example images from each category.

4 Proposed Neural Network Architecture

This study conducted numerous experimental trials before proposing the following architecture. While similar experiments have been conducted in previous studies [31, 33–35], the resulting test accuracy was unacceptable. Therefore, there was a need to design a new architecture. Figure 3 shows simple view of the proposed architecture for the proposed deep potato leaf blight classification.

The proposed deep learning structure in Fig. 4 consists of 14 layers, including two convolutional layers for feature extraction, with convolution window sizes of

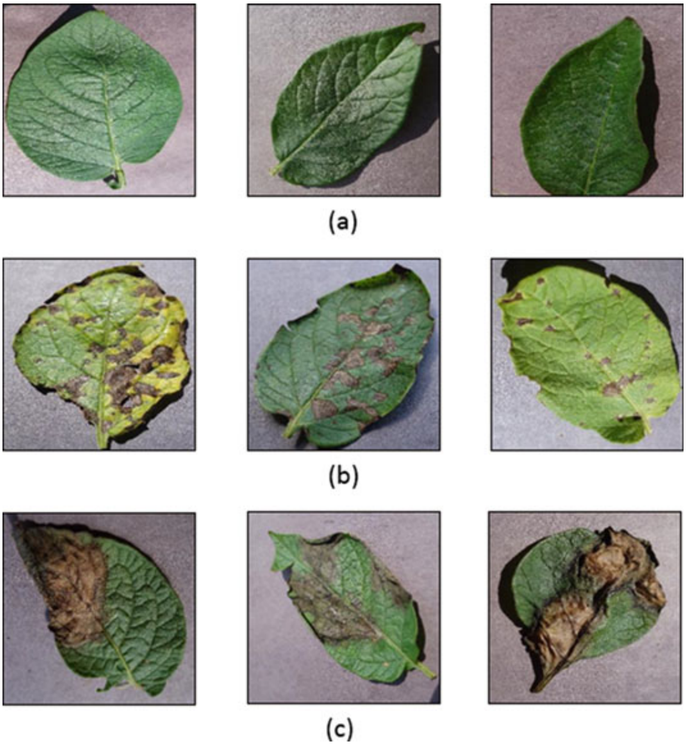

Fig. 2 Sample images from the potato leaf blight dataset, (**a**) healthy leaf category, (**b**) early blight leaf category and (**c**) late blight leaf category

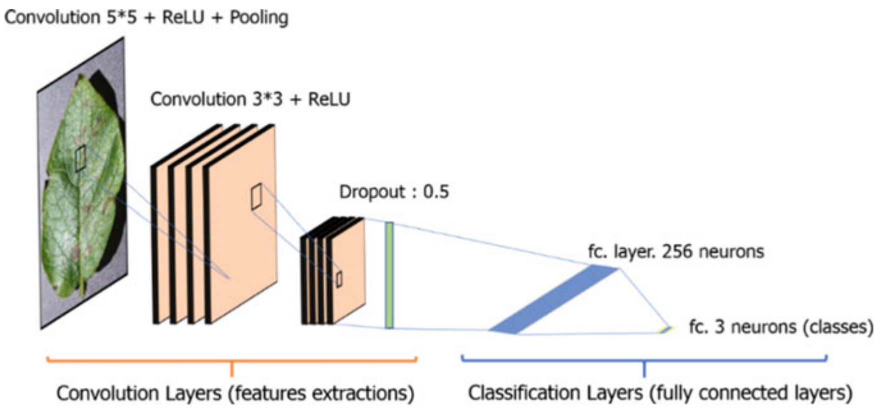

Fig. 3 The proposed deep learning structure

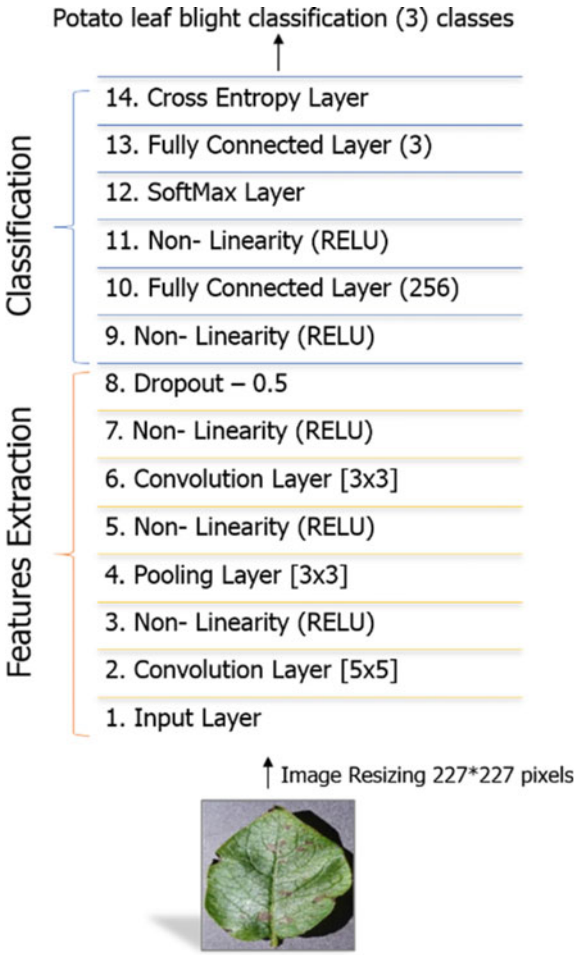

Fig. 4 Layer details of the proposed deep neural architecture

5×5 and 3×3 pixels, correspondingly, followed by two fully connected layers for classification. The first layer is the input layer, which accepts a 227×227-pixel image. The second layer is a convolutional layer with a window size of 5×5 pixels. The third layer is a ReLU, which is used as the nonlinear activation function. The ReLU is followed by intermediate pooling with sub-sampling using a window size of 3×3 pixels and another ReLU layer (layer five). A convolutional layer with a window size of 3×3 pixels and another ReLU activation function layer form layers six and seven. A dropout layer and ReLU is performed in layers eight and nine. Layer ten is a fully connected layer with 256 neurons and a ReLU activation function, and the final fully connected layer has 3 neurons to categorize the results into 3 classes for potato leaf blight classification. The model uses a softmax layer as layer number fourteen to determine the class membership, which predicts whether a potato-leaf image belongs to the healthy, early or late blight category.

5 Data Augmentation

The proposed architecture has an enormous amount of learnable parameters compared to the amount of images available in the training set. The original dataset contains 1722 images representing the 3 classes of potato leaf blight. Because of the large difference between the learnable parameters and the number of images in the training set, the model is highly likely to suffer from overfitting. Deep learning architectures achieve better accuracy when large training datasets are offered. One increasingly popular way to make such datasets larger is to conduct data augmentation (also sometimes called jittering) [36]. Data augmentation can increase the size of a dataset by up to 10 or 20 times its original size. The additional training data helps the model avoid overfitting when training on small amounts of data. Thus, data augmentation assists in building simpler, more robust, and more generalizable models [37]. This section introduces the common techniques for overcoming overfitting.

5.1 Augmentation Techniques

Augmentation Techniques are applied on order to overcome overfitting. This is done by increasing the number of images used for training. Data augmentation schemes are applied to the training set, and they can make the resulting model more invariant to reflection, zooming and small noises in pixel values. Images in the training data are transformed by apply augmentation techniques. The equation used for transformation is as follows:

Reflection X: Each image is flipped vertically as shown in Eq. (9):

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \cdot \begin{bmatrix} x \\ y \end{bmatrix}. \tag{9}$$

Reflection Y: Each image is flipped as shown in Eq. (10).

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} x \\ y \end{bmatrix}. \tag{10}$$

Reflection XY: Each image is flipped horizontally and vertically as shown in Eq. (11).

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix} \cdot \begin{bmatrix} x \\ y \end{bmatrix}. \tag{11}$$

Zoom: The content of each image is magnified in the training phase by first cropping the image from 0,0 to 150,150 and then scaling the result to the original image size (277 * 277 pixels) using Eq. (12):

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \text{Xscale} & 0 \\ 0 & \text{Yscale} \end{bmatrix} \cdot \begin{bmatrix} x \\ y \end{bmatrix} \tag{12}$$

Gaussian noise is considered additive noise, and it generally interferes with the grey values in digital images. The probability density function with respect to the grey values is shown in Eq. (13) [38]:

$$P(g) = \left(\sqrt{\frac{e}{2\pi\sigma^2}}\right)^{\frac{-(g-\mu)^2}{2\sigma^2}}, \tag{13}$$

where g is the grey value, σ is the standard deviation and μ is the mean. As illustrated in Fig. 5, in terms of the probability density function (PDF), the mean value is zero, the variance is 0.1 and there are 256 grey levels.

The data augmentation technique mentioned above were applied to the potato leaf dataset, increasing the number of images fivefold, from 1,722 to 9,822 images. This increase leads to a significant improvement during neural network training. Additionally, it reduces overfitting in the proposed design and makes it more robust

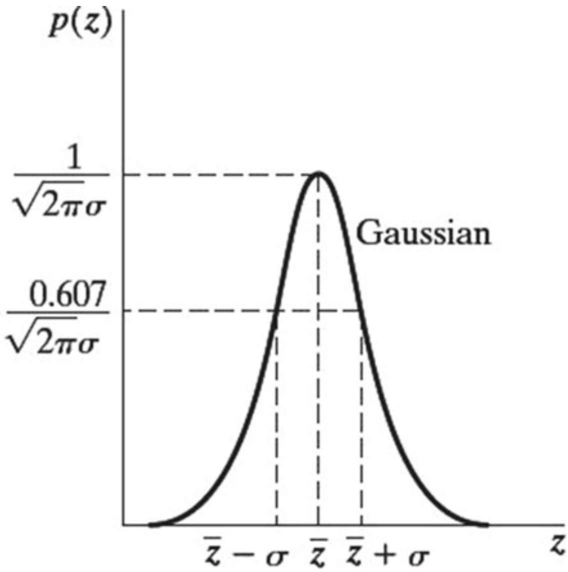

Fig. 5 The probability density function for Gaussian noise

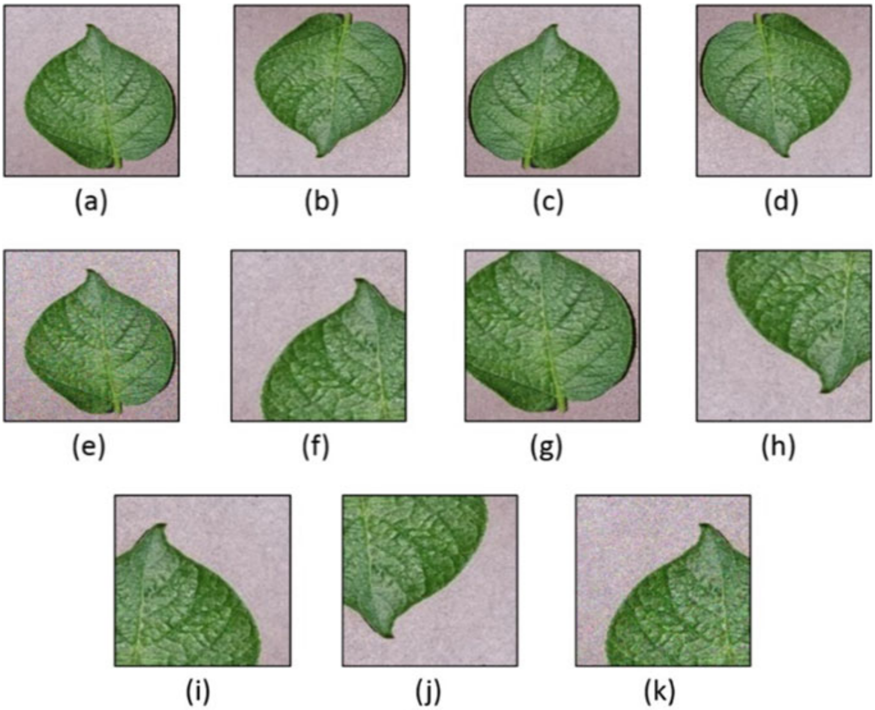

Fig. 6 Samples of augmented images: (**a**) original image, (**b**) reflected image around the X axis, (**c**) reflected image around the Y axis, (**d**) reflected image around the X-Y axes, (**e**) Gaussian noise applied to the original image, (**f**) zoomed image from [0,0] to [150,150], (**g**) zoomed image from [50,50] to [200,200], (**h**) zoomed image (**f**) reflected around the X axis, (**i**) zoomed image from (**f**) reflected around the Y axis, (**j**) zoomed image from (**f**) reflected around the X-Y axis and (**b**) zoomed image from (**f**) with applied Gaussian noise

during the testing and verification phases. Figure 6 shows the result of applying the described data augmentation techniques to a sample image from the dataset.

6 Experimental Results

The proposed architecture was implemented using MATLAB, and GPU specific. All trials were finalised on a computer equipped with an E52620 Intel Xeon processor (2 GHz) and 96 GB of memory.

To measure the accuracy of the proposed architecture for potato leaf blight classification using the proposed deep convolutional neural network, the dataset was divided into 2 sets of 80% and 20%; the 80% portion was used for training, while the remaining 20% was used for testing. The average overall testing accuracy for the original (non-augmented) dataset was 94.8%, while the average overall testing accuracy for the augmented dataset was 98%. A confusion (or error) matrix is considered a quantitative approach for characterizing image classification accuracy because it provides concrete evidence about the performance of a model. The confusion matrix for one of the testing accuracy trials on the original (non-augmented) dataset is presented in Fig. 7, while Fig. 8 shows a confusion matrix for the augmented dataset. The augmentation process has been applied into the training set which contains only 80% of the original dataset.

There are three types of accuracy scores [39]

- **Producer's Accuracy:** The ratio of images properly classified into class X with respect to the number of the images observed to be class X. This metric reflects the model's accuracy from the model's perspective and is equivalent to sensitivity.
- **User's Accuracy:** The ratio of images properly classified into class X with respect to the total number of images predicted as class X. This metric reflects the accuracy from the perspective of the model's user and shows its positive predictive power.
- **Overall Accuracy:** The ratio of properly classified images with respect to the total number of images.

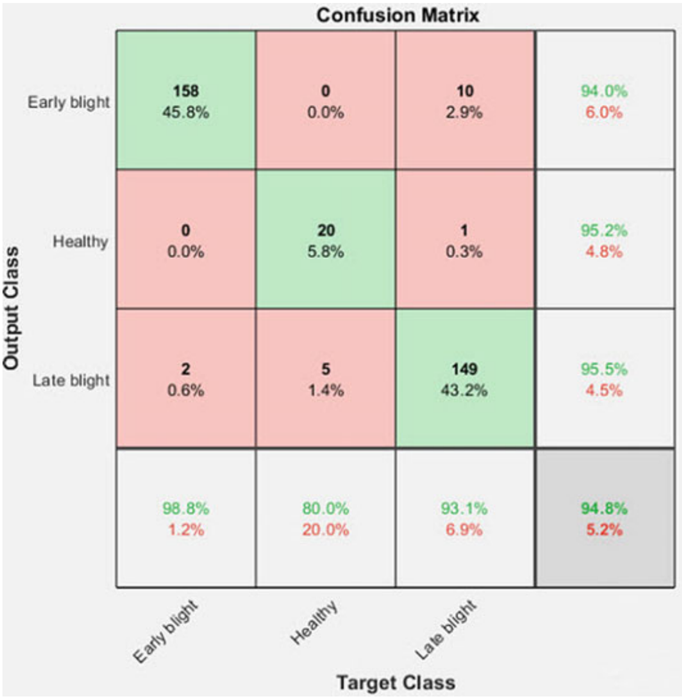

Fig. 7 Confusion matrix for one of the trials on the original (non-augmented) dataset

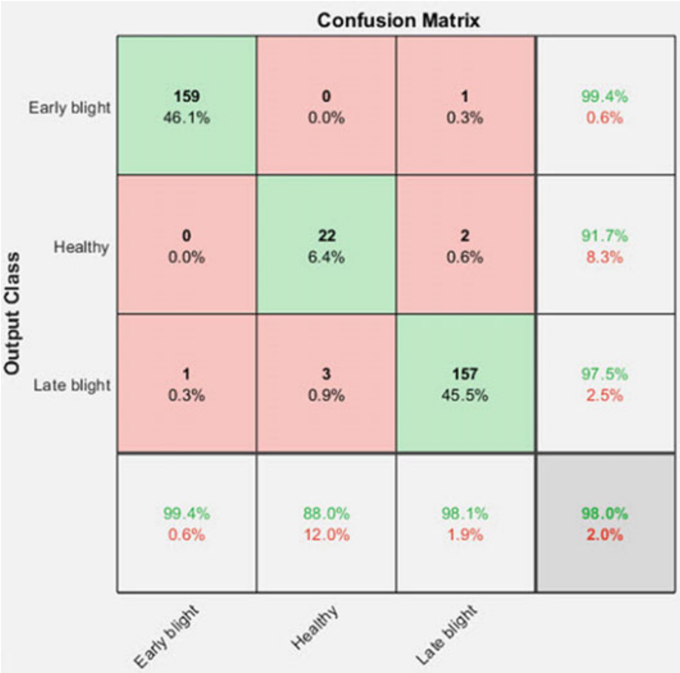

Fig. 8 Confusion matrix for one of the trials on the augmented dataset

Tables 1 and 2 present the producer's and user's accuracy for the original and augmented datasets, respectively.

Performance Evaluation and Discussion

To fully evaluate the performance of the proposed architecture, more performance measures must be investigated in this study. The most common performance metrics

Table 1 Producer's and user's accuracy for the proposed architecture on the original (non-augmented) dataset

	Early blight leaf (%)	Late blight leaf (%)	Healthy leave (%)
Producer accuracy	94.0	95.5	95.2
User accuracy	98.8	93.1	80.8

Table 2 Producer and user accuracy for the proposed architecture on the augmented dataset

	Early blight leaf (%)	Late blight leaf (%)	Healthy leave (%)
Producer accuracy	99.4	97.5	91.7
User accuracy	99.4	98.1	88.0

in the deep learning field are Precision, Recall, F1-score, Selectivity, Negative Predictive Value, Informedness and Markedness [40]. The calculations for these metrics are presented in Eqs. (14)–(20).

$$\text{Precision} = \frac{\text{TP}}{(\text{TP} + \text{FP})} \tag{14}$$

$$\text{Recall} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \tag{15}$$

$$\text{F1} - \text{score} = 2.\frac{\text{Precision . Recall}}{(\text{Precision} + \text{Recall})} \tag{16}$$

$$Selectivity = \frac{TN}{TN + FP} \tag{17}$$

$$Negative\ Predictive\ Value = \frac{TN}{TN + FN} \tag{18}$$

$$Informedness = Precision + Selectivity - 1 \tag{19}$$

$$Markedness = Recall + Negative\ Predictive\ Value - 1 \tag{20}$$

where TP is the number of true positive samples, TN is the count of true negative samples, FP is the count of false positive samples, and FN is the count of false negative samples from a confusion matrix.

Table 3 presents the performance measures for the proposed deep learning architecture on the datasets with/without the augmentation process, clearly showing that the performance measure results are better on the augmented dataset in terms of the achieved accuracies. The adopted augmentation techniques increased the dataset size, reduced overfitting, and finally, helped the model achieve better performance metrics and improved its overall testing accuracy.

Table 4 illustrates comparative results for related works and the proposed architecture. All the related works presented in Table 2 were applied to potato leaf blight datasets—not the same dataset used in our research, but the images are highly similar to those in our dataset. The results reveal that the proposed architecture achieved the highest overall testing accuracy (98%). Moreover, the proposed architecture is more robust and immune overfitting due to the augmentation process adopted in this study.

Table 3 Performance measures for the proposed deep learning architecture on the datasets with and without augmentation

	Without augmentation (%)	With augmentation (%)
Precision	83.71	94.75
Recall	88.44	93.22
F1-score	85.96	93.98
Selectivity	94.86	98.59
Negative predictive value	96.66	98.13
Informedness	78.58	93.35
Markedness	85.11	91.35

Table 4 Comparison results of related works and the proposed architecture

Related work	Year	Description	Accuracy (%)
[13]	2016	K-means clustering + segmentation based on colour, texture, and shape + backpropagation neural network	92.00
[14]	2017	K-means clustering + segmentation based on colour, texture, and shape + feed-forward neural network	95.30
Proposed architecture	2019	Deep convolutional neural networks	98.00

7 Conclusions and Future Work

Crop diseases are a common threat to food security in all nations, but with the artificial intelligence advances in detection and classification allow these threats to be maintained and eliminated at early stages rapidly and accurately. This paper presented a proposed deep learning architecture for potato leaf blight classification. The proposed architecture consists of 14 layers: two main convolutional layers for feature extraction with different convolution window sizes followed by two fully connected layers for classification. Augmentation processes were applied to increase the number of dataset images from 1722 to 9822, resulting in a substantial improvement in the overall testing accuracy. The proposed architecture achieved an overall mean testing accuracy of 98%. A confusion matrix showing all the different accuracy types has been presented in this research, and the performance measures are calculated and presented in this research. Finally, the results of a testing accuracy comparison between the proposed architecture and other related works were presented. The proposed architecture achieved better results than the related works in terms of overall testing accuracy. One prospect for future work is to apply transfer learning based on more advanced pre-trained deep neural network architectures such as AlexNet, VGG-16, and VGG-19. Using pre-trained architectures may reduce the computation time in the training phase and may lead to better testing accuracy.

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