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RESEARCH ARTICLE

DEEP DC-CNN PERFORMANCE FOR POTATO LEAF DISEASE DETECTION

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Abstract – Potato leaf diseases cause harm by reducing vegetative grade and yield, results to worldwide challenges. This is a primary cause of the scarcity of food and the rising expenses associated with food production. To detect the infections, an autonomous system built on machine learning evaluated against the most recent deep learning models, preferring to focus on more conventional methods. The present study introduced a Deep-learning based named Dual Channel Convolutional Neural Network (DC-CNN) model employs to detect the disease that are present in potato leaves. Plant Village Datasets are the input image's source data collection. To remove noise from input data, the data is pre-processed using the Kalman filter. Mask Region-based Convolutional Neural Networks, providing exact segmentation masks at the pixel level for each detected image, have been utilized in feature extraction. Furthermore, the images are classify using a Spiking Neural Network to determine whether the data given is normal or diseased. Finally, dual-channel convolutional segmentation is demonstrated, which enhances the performance of multimodal tasks and produces representation with attributes that are more valuable and reliable. The outcomes of the experiment prove the proposed DC-CNN strategy provides greater accuracy range of 99%, respectively.

Keywords *– Dual channel Convolutional Neural Network, Mask Region-based Convolutional Neural Network, Spiking Neural Network.*

1. INTRODUCTION

The human population have transported the Solanaceae family, which includes the cultivated potato (Solanum tuberosum), around the world [1]. It is one of the major vegetable crops that originated in South America [2]. The main cause of the world's food insecurity and hardship, as well as the rising costs of food production, is potato leaf diseases, which harm crops by reducing crop amount and excellence [3]. Diseases and disorders are types of factors that affect both crops and goods [4]. Rainfall, moisture, temperature, and lack of nutrients are the biotic factors that cause diseases due to algae, fungi, or bacteria are the biotic factors [5]. The most dangerous leaf diseases for potatoes are late and early blight, which cause major losses in productivity in most potato-growing regions [6].

Potatoes rank fourth in terms of global agricultural production of food crops, behind maize, wheat, and rice [7]. India produces 49.5 million tons of each year, ranking it as the second-largest producer of potatoes [8]. Approximately 28.9% of all agricultural crops produced in India are potatoes, making them the most versatile crop [9]. UP is India's first producer of potatoes, contributing more than 30.33% of the country's total output [10]. The FAO predicts that by 2051, there will be about 9.2 billion people of earth where approximately 71% for the necessity of food production to ensure a stable food supply [11].

The characteristics of early as well as late blight illnesses have been categorized using the chart cut approach and developed SVM model; nevertheless, the handmade feature-based classification is dependent on the attributes that are picked [12]. To identify and classify potato leaf infections, an autonomous system built on image processing and machine learning has been developed; however, it hasn't been evaluated against the most recent deep learning models, preferring to focus on more conventional methods [13]. Numerous CNN [14] have certain limitations in terms of recognizing crop species or crop illnesses in general, even if they have been trained and verified on photos of farmers leaving a specific location [15]. Therefore, the challenges are still in relay also the objective and contributions are as follows:

- The paper possesses a DC-CNN technique for segmentation for the detection of disease which is present in the potato leaves.
- Initially, the given dataset is preprocessed by using Kalman filter for removal of noise.
- Mask R-CNN is used for feature extraction which provides enhanced performance for the given image.
- SNN is used to classify to produce whether the given data is normal or diseased by producing high accuracy.

- Segmentation was done after the classification process for producing better Dice Score.

The remaining sections of the analysis are as follows: Section II provides a detailed presentation of the literature review. Section III provides an explanation of the proposed approach. Section IV contains the results and comments. Section V discusses the conclusion.

2. LITERATURE REVIEW

Developing primary objective of a number of frameworks that individuals have developed recently. In addition to the authors' name and year, the datasets they used, the method they employed, and a thorough evaluation the advantages and disadvantages of their current methods, this section offers a thorough examination of existing frameworks.

Tiwari et.al [16] deployed an automated technique adapted from the concept of TL to recognize and categorized diseases in leaves, such as disease and healthy. The suggested technique, 2153 was developed using images of potato leaves from a plant village collection, and it achieved a 97.8% accuracy rate. However, method could be updated in a better version.

Asif et.al [17] suggested a convolution neural network employed the established sequential model classification technique to identify potato diseases. Approximately more than three thousand images from the Kaggle dataset were gathered and combined by producing 97% with excellent accuracy. However real-time output should be considered for improving the accuracy.

Sholihati et.al [18] deployed a DL system that used Based on leaf conditions, the CNN incurring with VGG19 generated the highest overall accuracy of 91% for the four main types of diseases that afflict potato plants. However, the method acquires low accuracy.

Iqbal et.al [19] recommended an autonomous method that uses ML to spot and diagnose. 452 photos of healthy and diseased potato leaves were gathered from the freely accessible dataset, and classifier techniques were used to achieve an overall accuracy of 97%, however it was difficult.

Khalifa et.al [20] suggested two primary convolutional layers with varying convolution window sizes are among the 14 layers, which are succeeded by two completely connected layers for categorization. The dataset's image count increased from 1,723 to 9,823 images, significantly raising the testing overall accuracy of 98%. However, computational cost is high.

Rozaqi et.al [21] deployed to identify DL using the CNN along with Three different forms of data that yield 80% training and 20% testing are available on Kaggle under the tag of Plant Village Dataset. The overall accuracy obtained from this dataset is 97%. However, it possesses high complexity.

Shi et.al [22] suggested technique using actual HSI data from UAVs collected in both regulated and unregulated fields. Using the representative DL techniques using both testing and independent datasets using the representative DL approaches that are increasingly available and produce 98.08% accuracy but performance should be improved.

Mahum et.al [23] recommended algorithm is a novel approach which tackles and illustrates the way four infections in potato leaves were successfully identified and categorized using this method. When the algorithm was evaluated, it yielded an accuracy rate of 97.23% overall. However, experiments should be performed in simpler methods.

Bonik et.al [24] deployed the on the leaves of afflicted potato plants, signs of other diseases can be identified. The disease was predicted using a sequential model based on CNN, which had the highest overall accuracy of 94.2%. However, the suggested model should improve the accuracy performances.

Arshad et.al [25] recommended PLDPNet is a new hybrid deep learning network that is intended to automatically forecast illnesses of potato leaves. The hybrid method depends on the conceptual framework of vision transformers to arrive at a final forecast by achieving an overall highest accuracy of 98.66%. However, computational cost is high.

To develop additional techniques for the segmentation approach based on DC-CNN for the Potato leaf disease detection based on the previously provided related work. The methods used in the earlier studies were CNN, UAV, CNN which provided positive results such as overall accuracy of 91%, 98.08%, and 97%, respectively and these methods were also discussed in related works. However, some of the limitations of the existing works were as follows: high complexity; accuracy was compromised while localizing and segmenting the leaf disease and to further enhance the resilience of the model including a normalization term in the network loss function.

3. PROPOSED METHODOLOGY

The Kalman filter is used as a preprocessing step to denoise the incoming data. Following preprocessing, R-CNN is used to extract features from the preprocessed images. In order to identify the disease present in the potato leaf, the collected characteristics are then sent into SNN for classification and DC-CNN for segmentation.

3.1. Data Description

A public dataset called Plant Village contains 54,405 images of plant leaves, both weakened and in good condition, were collected under close supervision.

3.2. Preprocessing

The Kalman filter can handle situations including noisy measurements and complex system dynamics, it is particularly useful in such type of situations. By carefully determining the quality of both real and predicted data, it produces the best estimate. By repeating these prediction and constructive operations, the KF essentially improves its estimate of the system's state continuously, where precision and reliability are essential. Denote $i_t \in \mathbb{R}^x$ the true state and $j_t \in \mathbb{R}^y$ the observation, it is possible to provide The KF aims to tackle the linear dynamic model in the following approach.

$$i_t = Si_{t-1} + w_t,$$
$$j_t = Mi_t + v_t, \quad (1)$$

Where, $w_t \sim \chi(0, A)$,and $v_t \sim \chi(0, B)$ corresponding error matrices for states and observations; $S(n \times n)$and $M(m \times n)$are the observation and state transition matrices, respectively.

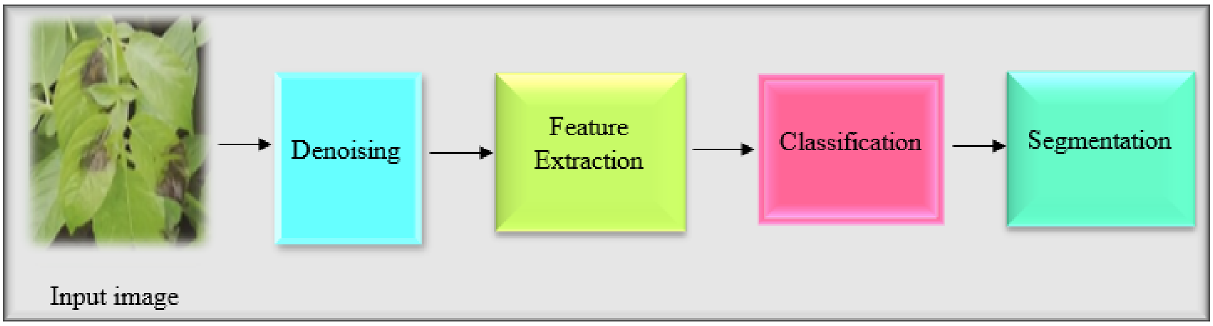

Figure 1. Proposed methodology overall workflow

S, M, A and B may alter with time, but are anticipated to stay unchanged. In KF, $(i_t|i_{t-1})$ and $(j_t|i_t)$are taken to be gaussians in both cases. The KF is composed of two steps: the "updating" step and the "prediction" step.

$$\hat{\imath}_{t|t-1} = S\hat{\imath}_{t-1},$$
$$V_{t|t-1} = SV_{t-1}S^T + A, \quad (2)$$

Let $\hat{\imath}_{t|t-1}$is previous time t, derived from the data at that specific moment, $t-1, V_{t|t-1}$be the state error covariance estimate, $\hat{\imath}_t$ is estimate posteriorwith observation j_t,$V_t$be the forecast and predictionisexpressed in Equation 2.

$$\hat{\imath}_t = \hat{\imath}_{t|t-1} + K_tV_t,$$
$$V_t = (Q - K_tP)V_{t|t-1}, \quad (3)$$

Where $K_t = V_{t|t-1}P^T(PV_{t|t-1}P^T + R)^{-1}$ is Kalman gain and $V_t = y_t - P\hat{\imath}_{t|t-1}$ is the innovation process. Updating of KF is Expressed in Equation 3. The probability of being observed $j_t$findings of $j_{1:t-1}$ could be obtained in Equation 4.

$$Z_t = p(j_t|j_{1:t-1}) = \mathcal{N}(v_t; 0, PV_{t|t-1}P^T + R) \quad (4)$$

$$[\hat{\imath}_t, V_t, Z_t] = Filter\ (\hat{\imath}_{t-1}, V_{t-1}, j_t, S, A, P, R) \quad (5)$$

It becomes clearly demonstrated in the research conducted above that the KF estimates the hidden states of the processes using a linear dynamic model.

3.3. Feature Extraction

The significant enhancement over the previous Faster R-CNN technique is Mask R-CNN. In Figure 2, the overall architecture is demonstrated.A Region Application Network subsequently employs the recovered feature maps to create ROIs on an image.

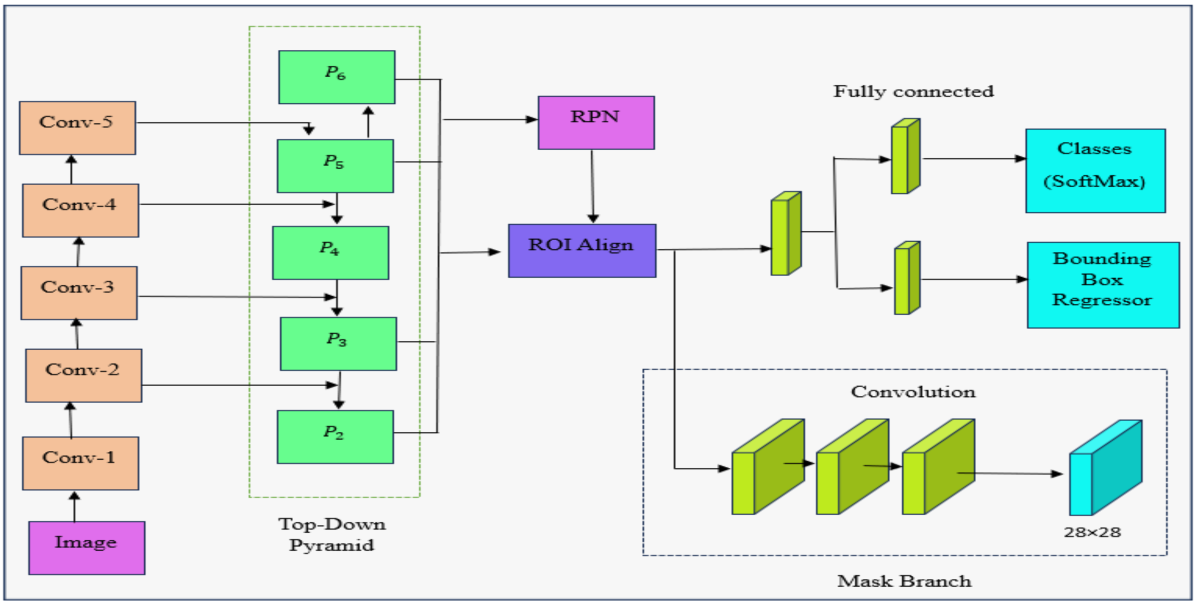

Figure 2. Mask R-CNN Architecture

The other layer calculates the likelihood that a target object will be present in the area box, the first layer establishes the locations of the region applications. The implementation of these layers—regression and classificationuse a 1 × 1 convolution filter for k number of region proposals, yielding output values for the corresponding layers. The parameterization of these k region solutions is done in relation to the reference boxes. Numerous region suggestions are produced by the RPN, among which may overlap for the same objects. Therefore, Non-Maximum Suppression was applied in order to decrease the quantity of created region proposals. Ultimately, a subset of the remaining region proposals was chosen for additional processing after they were arranged based on their categorization scores. A Fully Convolutional Networks was utilized to acquire the segmented masks, with a ROI pool size of 14 x 14 as opposed to 7 × 7. Following that, it is unsampled to a 28 x 28 size in order to get the final predicted masks.

3.4. Classification

An artificial neural network with characteristics similar to those of actual brin networks is called a spike neural network. Spike neural networks possess a universal linear structure. In addition to cognitive and neuronal states, time is included in the operational model of SNNs. Similar to convolutional multi-layer perceptron networks, which send information during every cycle of propagation, the SNN's neurons only send out information when their membrane potentials cross a threshold, or predefined value. The neuron strikes and releases an impulse that modifies the potentials of neighboring neurons when the membrane potential over the threshold

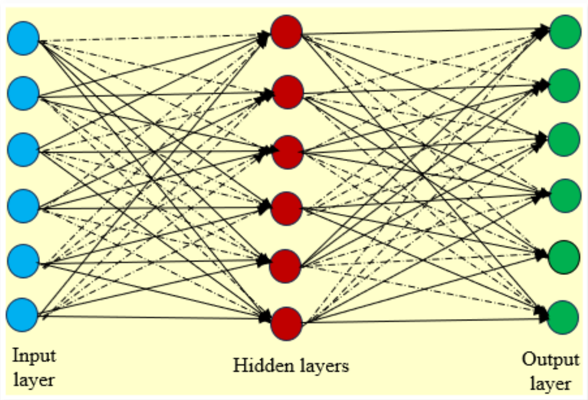

Figure 3. Design of SNN

The neural spikes' triggering time is as follows in Equation 6.

$$ft = \frac{FT_{max}}{1+\text{ex}\,(\sigma(129-i))} \tag{6}$$

Where, i is pixels image, $ft$is spike's firing time, σ refers coding parameter, FT_{max} is maximum time in firing. These systems include a four-layered SNN. The input layer, which consists of 465 × 465 neurons and alternating layers contain a large number of inhibitory neurons. Every input is a Poisson spike that passes into the excitatory neurons of the layers that follow. The maximum intensity pixels for tiring frequencies is specifically designed to range from 0 to 128 Hz.

$$P(t) = \sum_{i=1}^{N} w_i s_i\,(t) \tag{7}$$

In eachi^{th} input neuron, $P(t)$ is represented in Equation 7. Were, s_i is the spike image, w_i is weight and $w_i s_i(t)$is postsynaptic potential.$P(t)$ is greater than a specified threshold, ρ, then the output neuron spikes in Equation 8.

$$P(t) > \rho \tag{8}$$

The trace grows by 1 otherwise, it decays. Only when an excitatory postsynaptic neuron detects a spike perform weight updates being produced. The cost function F_c defined in Equation 9.

$$F_c = 0.4 \sum_j (p_j^c\,(t) - v_j^f\,(t))^2 \tag{9}$$

$$\frac{\partial F_c}{\partial w_{ij}} = -\sum_j e_i(t) \frac{\partial p_j^c(t)}{\partial w_{ij}} \tag{10}$$

Where, W_{ij} is the updated weight representation, $e_i(t)$ is i^{th} output neuron error, p^c and v^f are the firing rates which is represented in Equation 10. The output of the fourth layer, with dimensions of 50×464×464, is fed into the supervised convolutional deep learning model.

3.5. Segmentation

To enhance segmentation accuracy in the image segmentation technique, the DC-CNN employs the utilization of two distinct types of image channels, or modalities. Figure 3 depicts this architecture.

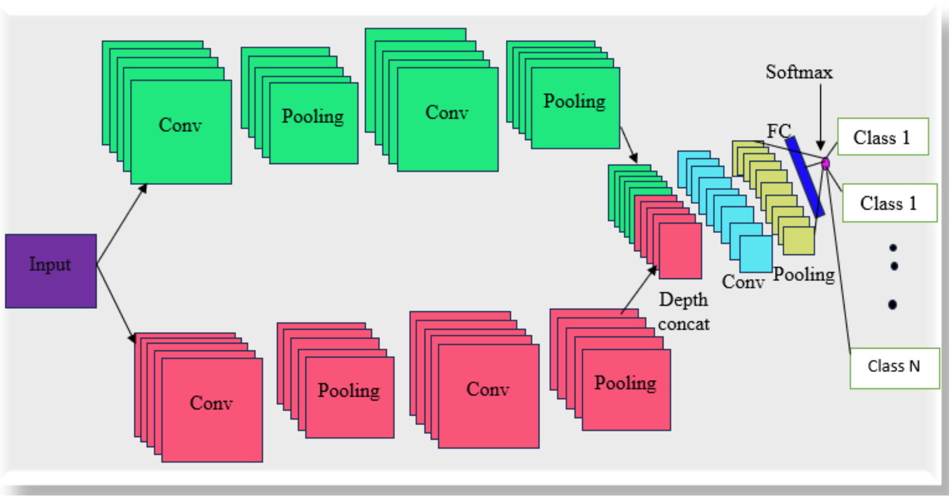

Figure 4. The structure and parameter of DC-CNN

There are primarily three components and they are the input data is in the first section. Followed by that there are two distinct CNN designs that are utilized, each with a unique set of convolution layers and kernels. Thus dual-channel CNN can yield two distinct feature sets. These two distinct convolution feature sets are subsequently connected using the inception model. Various convolution kernel sizes in the inception model correspond to distinct receptive fields, while resultant connections correspond to the fusing of distinct scale features. Different receptive fields are represented by different size convolution kernels in the inception model, and fusion of various scale features is represented by subsequent connections. In the third section, the final classification is obtained using a Softmax classifier achievements.

$$F_{Seg} = Conv(F_{Comb} + W_{Comb}) + B_{Comb} \tag{11}$$

$$S = Softmax(F_{Seg}) \tag{12}$$

Where, F_{Comb}, W_{Comb} and B_{Comb} are the final, kernels and bias of final convolution and F_{Seg} is the refined feature map in Equation 11. Softmax is applied to get the final segmentation mask in which S represent the segmentation mask in Equation 12.

4. RESULTS AND DISCUSSION

In this result analysis, leaf disease detection from plantvillage datasets. The SNN classify the leaf disease and then segment it by using DC-CNN which was evaluated using a wide range and the following are given below.

4.1. Performance analysis

It contains metrics that can be used to determine the effective the introduced model such as accuracy, specificity, precision, recall, and F1 score.

$$Accuracy = \frac{T_{pos}+T_{neg}}{Total\ no.of\ samples} \tag{13}$$

$$Specificity = \frac{T_{neg}}{T_{neg}+F_{pos}} \tag{14}$$

$$Precision = \frac{T_{pos}}{T_{pos}+F_{pos}} \tag{15}$$

$$Recall = \frac{T_{pos}}{T_{pos}+F_{neg}} \tag{16}$$

$$F1\ score = 2\left(\frac{Precision*Recall}{Precision+Recall}\right) \tag{17}$$

Here, T_{neg} denotes true negative, T_{pos} denotes true positive, F_{neg} denotes false negative and F_{pos} denotes false positive of the sample images. Evaluated metrices is given in the Table 1.

Table 1. Evaluation of DC-CNN

	Accuracy	Specificity	Precision	Recall	F1 Score
Proposed DC-CNN	99%	98.56%	98%	96%	97.99%

Performance analysis of DC-CNN model for potato leaf disease detection is shown in the form of graphical representation which is illustrated in Figure 5.

Figure 5. Performance analysis in Graphical representation

Testing and Training

Testing data evaluates the model's capacity for learning, whereas training data give the Deep learning model instructions. Using training data, excessive fitting can be prevented. Developing estimations on the testing data and comparing them to the actual labels enables the other to assess the model's performance.

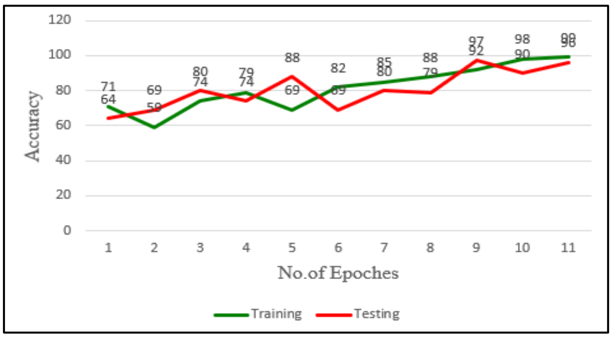

Figure 6. Accuracy curve of DC-CNN method

The accuracy curve in Figure 4 has a vertical axis that represents range accuracy and horizontal axis that shows epochs.

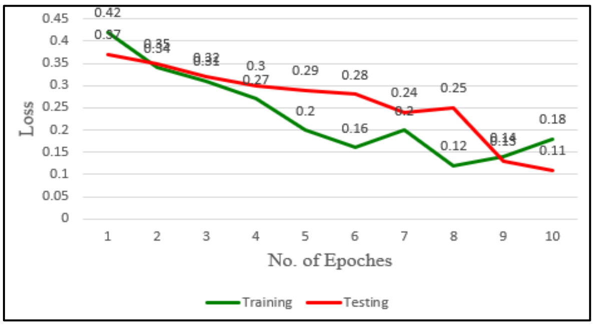

Figure 7. Loss curve of DC-CNN method

The proposed method obtains a high accuracy range in identifying the segmented images in the given input image.

4.2. Evaluating in Comparison

In this section, an assessment is also provided between the proposed approach and traditional deep learning networks. When evaluating this technique's performance with that of existing approaches, it turns out to be more productive.

According to Table 2, the proposed DC-CNN based technique improves an accuracy of 8.08%, 0.92% and 2.02% for CNN, UAV and CNN. From the above comparison, the proposed segmentation technique has improved in accuracy when compared to traditional methods.

Table 2. Table of Comparison between deployed and proposed method

Author	Methods	Accuracy (%)
Sholihati et.al [18]	CNN	91%
Shi et.al [22]	UAV	98.08%
Rozaqi et.al [21]	CNN	97%
Proposed	DC-CNN	99%

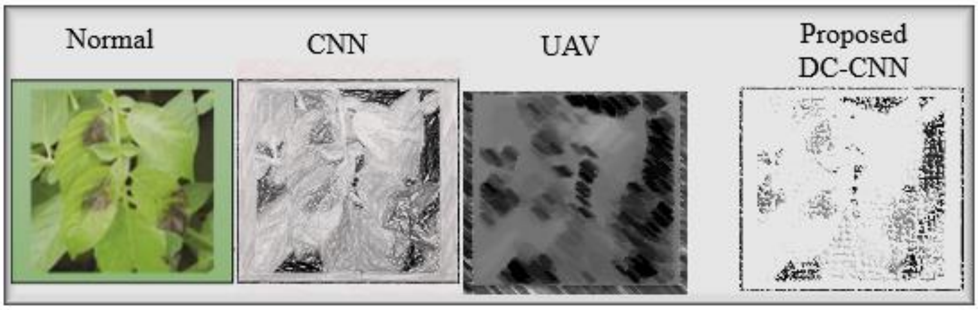

Figure 8. Segmentation results of potato leaf disease detection

In Figure 8. Represent highly effective and capable of finding many potatoes leaf disease. From the above comparison, the proposed segmentation technique has improved when compared to traditional methods.

5. CONCLUSION

In this paper, a novel DC-CNN technique is identified by potato leaf disease is employed. The initial image data collection is obtained from Plant Village Datasets. The data is pre-processed using the Kalman filter to eliminate noise from the input data. Feature extraction has implemented the usage of Mask R-CNN, that provides precise segmentation masks at the pixel level for every recognized image. In order to determine whether the information given is normal or diseased, the images are further classified using the SNN. In the final most, dual-channel convolutional segmentation has been demonstrated to improve multimodal task performance and yield representation with more trustworthy and valuable features. Future research should focus on automatically determining and categorizing the disease type and returning test findings and recommended medication to the smartphone.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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