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Regularization Proximity Censored Regressive Deep Reinforcement Learning for IoT aware Plant Disease Prediction

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***Abstract* - Agriculture is critical to food production worldwide and is an important part of the global economy, but is faced with significant threats to plants from diseases affected by climate change. Early and accurate prediction of plant diseases is more critical now than ever. The existing methods are not being able to address the complicated problems of multi label disease classification, we propose a new methodological approach to address these limits by using a new Regularized Proximity Censor Regressive Deep Reinforcement Learning (RPCRDRL) model. The new proposed model contains five stages: image acquisition using an IoT Framework, preprocessing using Hamann indexive total regularization filtering in order to eliminate "noise" to help provide accurate images, image segmentation using Moore proximity censored regression to isolate segments that suggest plant disease reference and isolate the ERGs (effectively removing other plant parts), 4 - feature extraction from shape, color, and texture features, and 5 - classification of plant diseases using Deep Reinforcement Learning (DRL) with the Ruzicka similarity index to improve accuracy and computing time. Our experimental results indicate that the RPCRDRL model improved disease identification of plant disease compared to traditional methods while also improving computation time. The RPCRDRL model significantly improved the model performance and real-time organization process for a real-time plant disease prediction with real-world data sets with accurate testing in agricultural scenarios including accuracy rates, precision rates, recall rates, F1 scores and prediction times.**

Keywords: Plant Disease Prediction, IoT, Hamann indexive total regularization filtering, Moore proximity censored regression method, Deep Reinforcement Learning, Ruzicka similarity index

I. INTRODUCTION

Plant diseases limit agricultural activity and crop growth, resulting in loss of yield, and ultimately impacting a nation's economic growth. Food production continues to grow due to population growth and climate change, warranting the need for an early detection mechanism for plant disease. There are a number of Machine Learning (ML) and deep learning (DL) models that have been developed to properly detect and classify plant diseases. However, there are still persistent challenges for these models in terms of accuracy, real-time prediction, time complexity and deployment in IoT-based environments.

Smart farming systems typically rely on Internet of Things (IoT) frameworks, where sensor units positioned throughout agricultural fields continuously take images of plant leaves. The collected timeless images are sent to a centralized place intended to make predictions of diseases. A hybrid model consisting of Convolutional Neural Networks (CNNs) and Conditional Random Fields (CRFs) [1] was proposed for the IoT-based plant disease recognition, the proposed model has some potential however, does not provide the desired prediction levels of accuracy for plant leave diseases. The Automated Plant Disease Detection and Crop Management model using the Spotted Hyena Optimizer and Deep Learning (APDDCM-SHODL) [2] aimed at improving productivity yield of crops and detection of disease within the IoT infrastructures, but the concerns surrounding time complexity and predicting accurately is still a challenge.

An Enhanced CNN (E-CNN) architecture [3] was developed for early diagnosis of common leaf diseases that had improved accuracy, but with no integration of IoT for intelligent classification in real-time. The Hierarchical Residual Vision Transformer model [4] was used for early identification of plant diseases by capturing invariant features in a more discriminative way. However, the Hierarchical Residual Vision Transformer long neglected to take an elegant approach to build the model for lightweight multitasking classification and did not model the assessment of severity. The Khill Herd-based Random Forest (KPh-RF) algorithm [5], developed to enhance accuracy, did not improve specificity and reduce errors.

Machine Learning (ML) algorithms were developed for sugarcane leaves [6] in developing the complete model to integrate feature extraction and enhance classification. While detection is improved, there is no decreasing time spent. Conference Paper for Multi-kernel Depthwise Separable Convolution (MDsConv), [7] enabled real-time detection because it captured a variety of spatial and representative features in automated images of crop species. However, the development of this model lacked feedback from IoT. A hybrid deep learning (DL) model [8], attempted to provide very early diagnosis, diagnosis and classification, and depicted a high prediction and classification model of crop diseases in general, but still lacked in reasonable processing time required for real-time implementation. The main objectives of this study are as follows

- To enhance the peak signal to noise ratio and minimize the error, Hamann indexive total regularization filtering method is employed to improve the image contrast by removing the noisy pixels.

- To minimize the time consumption of plant leaf disease prediction, Moore proximity censored regression method is employed for extracting the ROI. Followed by, color and texture features are extracted.
- To enhance the accuracy, deep Reinforcement Learning (DRL) are developed with the extracted features using that predicts leaf disease or healthy.

The paper is organized as follows: Section 2 reviews the relevant literature in the field. Section 3 describes the RPCRDRL model and its underlying processes. The experimental setup and datasets used are explained in Section 4. Section 5 compares performance across different methodologies using several evaluation metrics. Finally, Section 6 summarizes the findings and conclusions drawn in the work.

II. RELATED WORKS

A plant disease detection (PDDNet) models were developed in [8] for deep feature extraction and efficient plant disease identification. However, it failed to create a multi-object DL model for identifying plant illnesses with minimal time consumption. A deep learning-based approach was developed in [9] for the robust detection of sugarcane leaf diseases. However, the approach faced challenges in minimizing time consumption for sugarcane leaf diseases detection.

An attention-based multilevel DL architecture was designed in [10] for accurately classifying plant diseases. However, the designed technique increased the complexity of plant disease prediction. A CNN was developed in [11] for automatically detecting tea leaf diseases by collecting the large volume of images from different regions. But it failed to strengthen the model's accuracy and reliability. A novel LeafNet architecture was designed in [12] for detecting different types of diseases in groundnut leaves. However, integrating the architecture with IoT-based devices for monitoring and diagnosing leaf diseases was significant challenges.

An optimized automatic deep learning model was developed in [13] for accurate plant leaf disease classification through pre-processing and segmentation. However, it failed to minimize the computation complexity to improve the classification performance A Vision Transformer model was developed in [14] for timely and accurate disease management. However, it faced challenges in accurately identifying different crop growth stages and optimizing irrigation and nutrient application to improve precision agriculture and resource efficiency. A lightweight parallel depthwise separable model was developed in [15] using CNNs for accurate plant disease diagnosis. However, the enhancement of image quality through filtering techniques remained unaddressed. An Attention Score-Based Multi-Vision Transformer (Multi-ViT) model was developed in [16] for accurate plant disease classification. But it failed to explore hybrid approaches that with multi-leaf strategies to further develop the diagnosis accuracy. An integration of advanced transformer models within a federated learning method was developed in [17] for accurately diagnosing wheat leaf diseases. But the models faced the challenges in achieving time efficient disease prediction. An enhanced ECA-KDNet model was introduced in [18] for diagnosing apple leaf disease to efficiently enhance the accuracy and precision. But it failed to focus on analyzing the fine-grained disease identification and classification in complex contexts.

A novel Swin Transformer model was developed in [19] for fine-grained visual categorization of soybean leaf diseases. However, the model failed to minimize computational costs during soybean leaf disease prediction. In order to minimize the computation cost, three-dimensional convolutional neural networks (3D-CNNs) was developed in [20] for accurate disease prediction through spatial feature learning and consideration. An ensemble convolutional neural network was developed in [21] for predicting the mango leaf disease by consisting of various operations such as dataset collection, image preprocessing, noise removal, segmentation, feature extraction, and classification. However, it failed to consider the other deep learning methods for segmentation to achieve better results in detecting plant diseases. An improved version of the original MobileNetV2 model was designed in [30] for efficient deployment on resource constrained devices for plant disease detection and classification. But it failed to focus on applying advanced methods to enhance the model's adaptability and efficiency.

Existing models of plant disease detection are subject to constraints including excessive computational load, poor time efficiency, low adaptability in multi-crop/multi-leaf scenarios, lack of integration with IoT and precision agriculture, low quality of images produced, lack of fine-grained classification, and lack of generalization, making them less accurate, scalable, and unable to be used in a timely fashion.

III. PROPOSED METHODOLOGY

Timely prediction and management of plant diseases are essential in modern agriculture to maintain crop health, achieve higher yields, and safeguard food security. Traditional approaches to plant disease detection often fall short in terms of scalability, accuracy, and efficiency. To address this challenge, this paper introduces an advanced machine learning framework, termed the RPCRDRL model, designed for precise identification and diagnosis of various plant diseases. The architecture of the RPCRDRL model is illustrated in Figure 1.

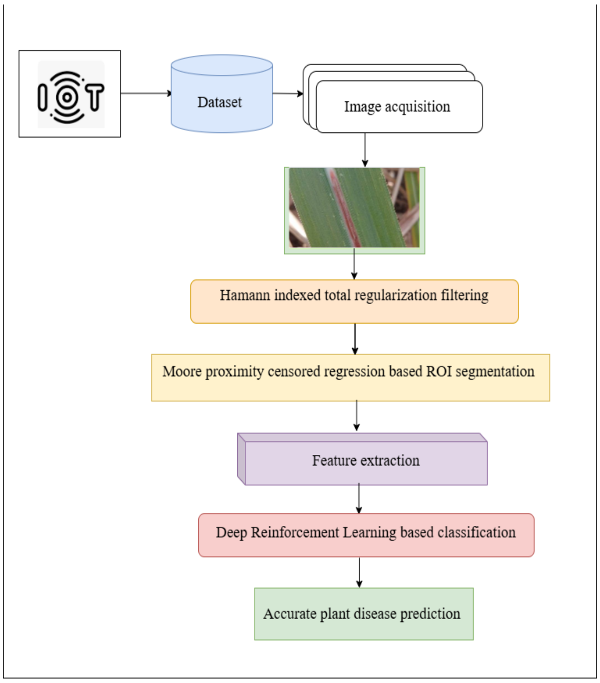


Figure 1 architecture diagram of proposed RPCRDRL model

Figure 1 illustrates the architectural framework of the proposed RPCRDRL model, developed to ensure precise prediction of plant diseases in agriculture. The model integrates key stages, including image acquisition, preprocessing, feature extraction, and classification, each contributing significantly to enhancing the model's predictive accuracy. Detailed explanations of these processes are provided in the subsequent subsections.

A. Image acquisition

Image acquisition refers to the process of capturing and collecting images for analysis, and processing. An IoT-based system (i.e. camera) is implemented in the agriculture field for capturing plant leaf images. The IoT system captures images of the plant leaves. These images are taken under regular lighting conditions and better resolution to detect disease symptoms. Once the images are collected, it uploaded to an image database i.e. Sugarcane Diseases Dataset for further analysis https://www.kaggle.com/datasets/prabhakaransoundar/sugarcane-disease-dataset. The dataset consists of 300 sugarcane leaves images for organizing into three folders namely Bacterial Blight, Healthy, and Red Rot, each folder containing 100 leaf images. These collected sugarcane leaf images are used for disease prediction in the agriculture domain.

B. *Hamann indexive total regularization filtering based preprocessing*

After the image acquisition, preprocessing is carried out to enhance the image quality by applying a Hamann indexive total regularization filtering method. Image preprocessing refers to the process of enhancing the image contrast by filtering the noises. Total regularization filtering method is employed in image processing tasks to remove noisy pixels while preserving edges. Let us consider the input sugarcane leaf image $SI_1, SI_2, \dots, SI_n$ taken from the dataset. The number of pixels in each image is indicated by $P_1, P_2, P_3 \dots P_m$. The filtering method selects a window with the size of $k * k$ as shown in figure 2

P_1	P_2	P_3
P_4	P_5	P_6
P_7	P_8	P_9

Figure 2 $k * k$ Filtering window

Figure 2 depicts the $k * k$ filtering windows where the number of pixels $P_1, P_2, P_3 \dots P_m$ are located within the filtering window in the form of rows and columns. After arranging the pixels, the absolute difference or total variation between the current pixels and the adjacent pixels are measured with the help of the Hamann similarity index. It is a statistical method used for evaluating the similarity between the pixels.

$$hs = 1 - \left[\frac{2\,|P_j\,\Delta P_k|}{n}\right] \qquad (1)$$

$$Z = \{hs > T \ ; Normal\ pixels\ hs > T \ ; Noisy\ pixels \qquad (2)$$

Where, hs indicates a Hamann similarity index, P_j denotes pixels within the filtering window, P_k denotes adjacent pixels in the images, 'n denotes a total number of pixels within the image, $P_j\,\Delta P_k$ and indicates a total variation between the pixels. The similarity index 'hs' returns a value from 0 to 1. The algorithm of the Hamann indexive total regularization filtering based image preprocessing is given blow.

```
Algorithm 1:   Hamann indexive total regularization filtering based preprocessing
Input: database $DB$, number of plant leaf images $SI_1, SI_2, SI_3, \dots\dots SI_n$
Output :Quality improved leaf images
Begin
    Collect plant leaf images $SI_1, SI_2, SI_3, \dots\dots SI_n$ from database
    For each plant leaf images $SI_i$
        Arrange the pixels in filtering window
        For each pixels $P_j$
            For each adjacent pixels $P_k$
                Compute the Hamann similarity index '$hs$' using (1)
            End for
        End for
        If ($hs < T$) then
            Detect the noisy pixels and it removed
        else
            Identify the normal pixels
        End if
    End for
    Return (Obtain quality enhanced plant leaf image)
    End for
End
```

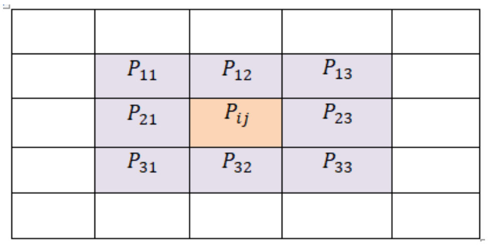
The approach to enhance image quality by performing noise pixels recovery is displayed in Algorithm 1. To begin with, some images of sugarcane leaf are taken from the available data set. Then, the pixels of these images are listed and grouped inside the filtering window. After obtaining a pixel and its co-existing pixels, we will compute the Hamann similarity index to analyse the variances of the images. Then with the variance label a pixel as normal or a noisy pixel, and thus removing the noisy pixels to produce improved quality images.

C. Moore proximity censored regression method

After image preprocessing, segmentation must be performed on the processed leaf images to extract the Region of Interest (ROI). The purpose of segmentation is to separate the meaningful regions from the background using the Moore proximity-based censored regression method. Censored regression is a machine learning technique that allows for the extraction of segments by evaluating the characteristics of pixel values to isolate the ROI.

Censored regression is a statistical approach that is used to analyze feature relationships by filtering final feature subsets based on a set censoring threshold. In a censored regression, some data points are considered exact values, whereas other data points are considered excluded when the data point is above or below the censoring threshold. The censoring threshold functions as a dividing line between left-censored and right-censored data. Left-censored data is used when observed values fall below the threshold, whereas right-censored data is used when observed values exceed the threshold.

The Moore proximity algorithm uses two-dimensional square lattice with a central cell and eight neighbors. Each cell's proximity is represented by a group of pixels. The eight adjacent pixels of the cell are included in the cell's Moore neighborhood: P1,P2,P3,P4,…,Pm.



	P_{11}	P_{12}	P_{13}	
	P_{21}	P_{ij}	P_{23}	
	P_{31}	P_{32}	P_{33}	

Figure 3 orthogonally aligned pixels

Figure 3 symbolizes orthogonally aligned pixels in the form of row and column. First, the central pixel positioned in two dimensional spaces (P_{ij}) and the orthogonal pixels connectivity is computed. Followed by, the pixel connectivity is measured through the mean deviation computation process.

$$PC = \frac{\sum_{i=1}^{m} |P_{ij} - P_{nn}|}{\sigma_{bet}} \qquad (3)$$

Where, PC denotes a results of the pixel connectivity, P_{ij} denotes a central pixel, P_{nn} indicates a neighboring pixels, σ_{bet} denotes a deviation between the two pixels. The censored regression analyzes the pixel connectivity value by setting the threshold function ‘ δ’ to separate right and left censoring results. If the pixel connectivity ‘PC’ greater than the threshold ‘δ and then the right censoring is occurred and the pixels are more similar. Otherwise, the left censoring is occurred and the pixels are removed.

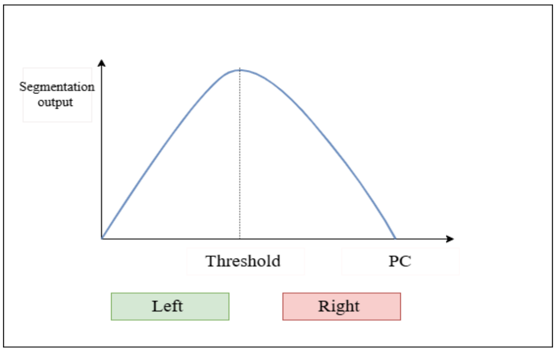


Figure 4 censored regression based segmentation output

Figure 4 illustrates the censored regression outcome where pixel connectivity is measured to enhance the segmentation process. The censored regression function is utilized to generate the segmented region output, ensuring improved pixel connectivity within the region of interest. This approach effectively identifies and isolates the relevant disease affected region while removing the remaining portions of the image, resulting in a more accurate segmentation.

```
Algorithm 2:  Moore proximity censored regression method
Input: Number of preprocessed input sugarcane leaf image $SI_1, SI_2, SI_3, \ldots . SI_n$
Output:  Segment the infected region i.e. ROI image
Begin
Collect the pre-processed sugarcane leaf image $SI_i \in SI_1, SI_2, SI_3, \ldots . SI_n$
  For each $SI_i$ do
    for each center pixel $P_{ij}$
      for each neighboring pixel $P_{nn}$
        Measure the pixel connectivity using (3)
      End for
    End for
  End for
    $if (Right\ censoringres\ )$then
      extract ROI
    else
      find dissimilar pixels
    End if
Return (segmented ROI)
End
```

Algorithm 2 describes the step-by-step process of Moore proximity censored regression for ROI segmentation. The connectivity between the center and neighboring pixels are estimated. The regression function assigns the threshed and separates the right and left censoring results. The right censoring results are used for finding the ROI region. Finally, the ROI is extracted by removing the irrelevant regions from the sugarcane leaf image to reduce the time consumption of plant leaf disease prediction.

IV. RESULTS AND DISCUSSION

In this section, experimental assessment of the proposed RPCRDRL model and existing methods Hybrid CNN with CRF [1], APDDCM-SHODL [2] and E-CNN [3] are implemented using python high level programming language with Sugarcane Diseases Dataset https://www.kaggle.com/datasets/prabhakaransoundar/sugarcane-disease-dataset. The dataset contains 300 images of sugarcane leaves, divided into three categories namely Bacterial Blight, Healthy, and Red Rot, with each category having 100 images.

Quantitative performance evaluation is done using several metrics, including peak signal-to-noise ratio (PSNR), plant leaf disease prediction accuracy, precision, recall, F1-score (or F-measure), specificity, and prediction time.

Peak Signal-to-Noise Ratio (PSNR): PSNR is defined as the ratio between the maximum possible pixel intensity and the mean square error (MSE). The MSE is calculated from the original leaf images and the preprocessed images that had their quality improved. PSNR and MSE are calculated using the following formulas:

$$\mathrm{PSNR} = 10 * \log_{10}\left(\frac{\mathrm{P_M}^2}{\mathrm{Mse}}\right) \tag{4}$$

$$\mathrm{MSE} = [\mathrm{OSI_i} - \mathrm{SSI_A}]^2 \tag{5}$$

Where, psnr denotes a peak signal-to-noise ratio, $\mathrm{P_M}$ symbolizes a maximum possible pixel value (i.e. 255),MSE denotes a mean square error, '$\mathrm{OSI_i}$' denotes an original leaf image size, $\mathrm{SSI_A}$ indicates a pre-processed leaf image size. The peak signal-to-noise ratio is measured in terms of decibel (dB). Table 1 lists the PSNR values for the leaf images in different sizes

Table 1 comparison of peak signal to noise ratio

Leaf image size (MB)	Peak signal to noise ratio (dB)			
	RPCR DRL	Hybrid CNN with CRF	APDDCM-SHODL	E-CNN
3.39	70.06	62.55	65.20	64.60
5.14	68.13	60.89	64.04	63.52
4.66	74.15	65.20	68.13	66.91
4.82	69.04	59.50	62.11	60.89
5.49	70.06	60.17	64.04	63.52
5.25	69.04	62.55	64.15	62.81
6.71	74.15	64.60	69.04	67.30
9.96	66.54	57.24	61.68	60.52
7.30	67.30	58.58	64.04	62.55
11.45	69.04	59.18	62.11	60.52

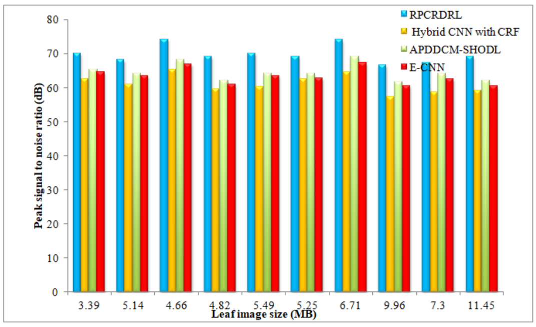


Figure 5 graphical representation of peak signal to noise ratio

Figure 5 shows a graphical comparison of peak signal-to-noise ratio (PSNR) versus image sizes of sugarcane leaf images in the dataset. On the graph, the image sizes are listed along the horizontal axis and PSNR values are listed along the vertical axis. Comparison was performed between the proposed RPCRDRL model and 3 other models: Hybrid CNN with CRF [1], APDDCM-SHODL [2], and E-CNN [3].

The results show that the RPCRDRL model has greater PSNR values than all of the other methods. This increased value is a result of the Hamann index–based total regularization filtering performed during preprocessing which increased image clarity and quality by removing epochsof noisy pixels. The Hamann similarity index was going to be calculated and presentedfor every pixel with its neighboring pixels (hisym - D were the reference images, and the hysc would be the noisy pixels or index of similar pixels) to distill out differences, higher differences would indicate noise which would be removed, producing consistent images across the dataset. Various size images were experimented with, then PSNR values of the RPCRDRL model were compared to the baseline methods. Taking averages from ten experimental runs show that relative to methods [1], [2], and [3], the RPCRDRL method achieves PSNR improvements of 14%, 8%, and 10%, respectively. Accuracy: Accuracy is evaluated as the ratio of the number of plant leaf images correctly predicted as Bacterial Blight, Healthy, and Red Rot, respectively, relative to the total number of input plant leaf images taken from the dataset. Mathematically, the overall accuracy is estimated below,

$$\mathrm{DPA} = \left(\sum_{i=1}^{n} \cdot \frac{\mathrm{CP}}{\mathrm{SI_i}}\right) * 100 \tag{6}$$

Where DPA indicates a plant leaf disease prediction accuracy, n represents the number of plant leaf images, CP denotes the number of leaf images correctly classified to the total number of sugarcane images '$\mathrm{SI_i}$'. The overall accuracy is measured in percentage (%). Table 2 shows the accuracy performance .

Table 2 comparison of plant leaf disease prediction accuracy

Number of leaf images	Accuracy (%)			
	RPCR DRL	Hybrid CNN with CRF	APDDCM-SHODL	E-CNN
30	96.66	83.33	90	86.66
60	93.33	85	90.05	88.05
90	95.65	86.66	91.56	89.45
120	96.98	88.33	91.75	89.77
150	97.56	85.33	91.33	88.05
180	96.74	86.11	91.66	89.45
210	97.88	83.8	92.05	88.62
240	95.77	84.58	91.65	89.35
270	97.45	85.55	92.59	90.74
300	97.12	86.33	92.56	89.87

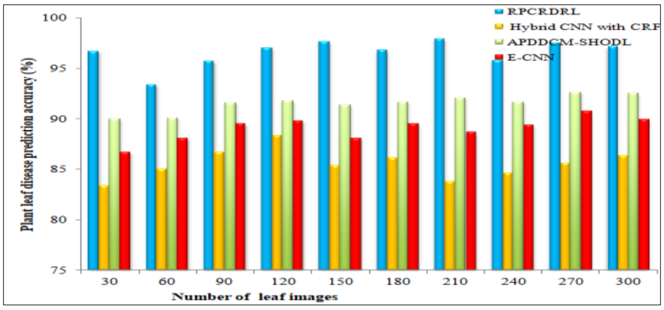


Figure 6 graphical representation of plant leaf disease prediction accuracy

Figure 6 illustrates the comparison analysis of plant leaf disease prediction accuracy versus the sugarcane leaf images samples. As shown in figure, the 'x' axis represents the number of leaf images, while the vertical axis indicates the accuracy of four methods namely RPCRDRL model and existing methods Hybrid CNN with CRF [1], APDDCM-SHODL [2] and E-CNN [3]. The examined results designate that the RPCRDRL model achieved higher accuracy when compared to the existing methods. For example, with 30 images, the RPCRDRL model achieved an accuracy of 96.66%, whereas the existing methods [1] [2] [3] were achieved accuracies of 83.33%, 90% and 86.66%, respectively. Various performances were observed across all images. The performance of proposed RPCRDRL model is compared to the existing methods. The overall comparison results shows that the performance of accuracy using RPCRDRL model is improved by 13%, 5%, and 8% when compared to the existing methods [1] and [2][3] respectively. This is because of applying Ruzicka indexive deep reinforcement learning model. First, different features such as texture and color features are given as input to the Ruzicka indexive deep reinforcement learning. The deep learning classifier model is employed to analyze the feature vectors through the Ruzicka similarity index and provides the classification results as Bacterial Blight, Healthy and Red Rot. Subsequently, rewards are assigned to the classification results based on error rate. Following the reward measurement, Q-value gets updated and decision-making process is executed after the convergence. This process enhances the accuracy of the different classes of the disease prediction

V. CONCLUSION

A IoT integrated RPCRDRL model is proposed to provide accurate and fast plant disease detection. The IoT capabilities used to collect the images of plants leaves is performed in real time, and it is processed for performance assessment. The image processing component allows for preprocessing of images to improve contrast levels and reduce noise which improves peak signal-to-noise ration. The residual image is then segmented, and ROI is marked for feature extraction for reducing computation for diseased prediction. The features are extracted and assessed with a deep reinforcement learning mechanism along with Ruzicka similarity index to provide an accurate prediction. A comprehensive experimental evaluation is conducted using various performance metrics, such as peak signal-to-noise ratio, accuracy, precision, recall, F1 score, specificity, and plant leaf disease prediction time. The model proposed with an RPCRDRL framework aids to boost prediction accuracy and reduces prediction time for the existing images. Future work will seek to extend the RPCRDRL model to enable real-time disease detection in various crop species in diverse environmental conditions by integrating multimodal data - additives such as soil and climate parameters from different data sources, framework optimization for edge computing and low-power IoT devices - not only allows for scalability and adaptability for real-world variables, they will also lead to improvements in the prediction accuracy.

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