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AN OPTIMIZED DEEP REINFORCEMENT LEARNING FOR RICE DISEASE PREDICTION

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Abstract:
Agriculture experts have put a lot of effort into protecting rice plants. However, a thorough investigation of the plant disease issue has not been carried out. The accurate identification of rice infections is essential for avoiding the disease's substantial detrimental consequences on crop production. However, the current methods for diagnosing diseases in rice are neither precise nor effective, and sometimes additional equipment is needed. It is crucial to find any illness early on and before the damaged plants receive the necessary treatment in order to maintain the healthy and normal growth of the rice plants. It makes sense to have an automated system since manual illness detection requires a lot of time and work. This study describes a machine learning-based method for detecting diseases in rice leaves. This research identifies leaf smut, bacterial leaf blight, and brown spot illnesses as three of the most prevalent diseases affecting rice plants. The input consisted of clear pictures of damaged rice leaves on a white backdrop. For that, we proposed an Optimized Deep Reinforcement Learning (Optimized DRL) approach. Following the appropriate pre-processing, feature learning is performed by African Buffalo Optimization (ABO) algorithm. With the optimal features, Deep SARSA algorithm is employed for the classification purpose. After 10-fold cross-validation, the decision tree method produced results on the test dataset with an accuracy of above 97%.

1. Introduction

For any nation, the agricultural output production is quite essential [1]. According to the Food and Agriculture Organisation of the United Nations (FAO), in order to feed 9 billion people by 2050, agricultural production would be 70% more in demand [2]. More over 50% of people globally rely on rice as one of their main food sources, and it has made a substantial contribution to global food security [3]. Therefore, the economy and politics are greatly impacted by rice yield. Food security is crucial for developing nations because food shortages can impede economic growth and possibly cause social upheaval [4]. On the other hand, despite the fact that industrialised nations have an abundance of resources for agricultural products, agricultural plant protection, including crop yield prediction and disease control using botany, should also be treated seriously [5]. To sustain crop output and provide food security, it is crucial to forecast rice yield and illnesses. In agriculture, rice is a crucial crop. Crop diseases, on the other hand, can drastically lower crop productivity and quality, posing a serious danger to global food supplies. So, disease prevention is essential for the production of rice. Correct and prompt illness diagnosis is essential for effective disease management because it enables timely implementation of pesticide control strategies. Manual judgement based on illness appearance is now the most used technique for diagnosing diseases in rice crops [6]. In the area, there aren't enough workers with the necessary abilities to finish such projects on time. Therefore, a more effective and practical way of diagnosing rice illness is needed.

Using computer vision technology, researchers have been able to predict crop yields, identify weeds, identify crop nutritional deficiencies, and detect crop nutritional deficiencies. Image processing, pattern recognition, support vector machines, and hyperspectral detection are just a few of the computer vision techniques that have been applied to the diagnosis of agricultural diseases [7]. To distinguish between healthy and unhealthy tomatoes, cluster analysis was applied to multi-spectral remote sensing photographs of tomato fields. A support vector machine was used to extract the form and textural characteristics of the rice bacterial leaf blight, sheath blight, and blast. The damaged leaves of various crops were identified using a genetic algorithm and a support vector machine. Naive Bayes is utilized to categorise rice brown spot, bacterial blight, and blast after detecting the RGB value of an afflicted area [8]. Wheat leaf rust and tomato mosaic disease have both been identified using infrared thermal imaging technology that offers crop temperature information. Despite the fact that some of these technologies may diagnose crop diseases with reassuringly high accuracy, the majority of them rely on manually extracting disease symptoms. As a result, the capacity to convey ideas is constrained, and generalising from results is challenging. Additionally, certain techniques need for specialised equipment that isn't always accessible to users. Applying these techniques to diagnose agricultural diseases is challenging because of all these limitations.

To get over these issues, deep learning technology can be used in crop disease diagnostic techniques [9]. Deep learning has been a popular tool for object identification, content recommendation, and picture categorization in recent years. In fact, researchers have utilised deep learning to find illnesses in a variety of crops. An in-field automated disease diagnostic system was suggested that may identify and localise illnesses affecting wheat. In order to identify spot illness in sugar beetroot leaves, first used a convolutional neural network (CNN), Faster R-CNN, to the pictures of the leaves. In order to diagnose diseases, SoyNet, which was applied to photographs of soybean leaves. Numerous other crops, including tulip, cassava, tomato, and millet, also benefit from the use of deep learning for disease detection. Deep learning has also been used to identify illnesses in rice crops. For instance, integrated Reduced MobileNet with a depthwise separable convolution architecture. There have been a number of claims regarding recognition accuracy. In order to classify rice illnesses employed Enhanced VGGNet with Inception Module using migration learning, which had a 92% accuracy rate. A two-stage tiny CNN architecture is suggested that, with reduced model sizes, achieved 93.3% accuracy. The correctness has been improved by certain attempts. For instance,developed three distinct CNN architectures that combine contextual non-image meta-data using a dataset of five crops, 17 illnesses, and 121,955 photos.

For early discovery of the damaged plants, prompt treatment, and most importantly, the development of future plans to prevent the illnesses to minimise losses, monitoring the diseases, their occurrences, and frequencies is crucial [10]. Crop disease management in Bangladesh has historically involved manual identification of any abnormality in plants, expert assessment of that irregularity as a disease, and then the recommendation of the right course of action. When vast farms are taken into account, this set of responsibilities becomes quite difficult. Additionally, it adds more time and work. On the other hand, collecting photos of the plants' afflicted areas and using them to train a model improves disease identification and categorization.

In a word, deep learning is a promising technique that can diagnose numerous crop diseases with great accuracy. There is currently only a small amount of study on the use of deep learning to rice illnesses. There are many different forms of rice diseases that have been seen in rice fields, including brown spot, false smut, neck blast, sheath blight, and rice leaf blast. The objective of this study was to improve rice disease diagnostics in terms of precision, efficacy, price, and convenience.

2. Literature Review

In the past, attempts have been made in a number of nations to define the link between the severity of the rice blast and the surrounding environment using both empirical and explanatory simulation models generated only using the traditional regression analysis, i.e. in Korea [11]-[13]. Due to two plausible reasons, however, farmers have only used a small portion of these models to manage rice blast: first, growers and farmers tend to be risk-averse and are not fully persuaded to use disease forecasting tools; and second, the mathematical relationships between environmental factors and the particular stages of the rice blast infection cycle are not fully understood. This makes traditional modelling techniques like multiple regression challenging.

There have been several more unsuccessful attempts to establish a quantifiable link between weather and disease infection from field investigations. Infection could not be linked to any particular sequence of weather occurrences, and Davis et al. could not discover any evident correlation between illness severity and weather [14]. In their 2-year field investigation in Australia, Chakraborty and Billard used multiple linear regression (REG) analysis to demonstrate that the REG model was not equally successful in predicting infection episodes [15]. The REG model cannot sufficiently explain infection at a field location in Queensland, Australia, according to a subsequent independent investigation [16]. According to these research, the REG models had a weak capacity to generalise across field locations and years, even while they could explain illness development at a specific field site for certain years. Therefore, a variety of modelling techniques have been used to increase the knowledge (i.e. prediction) of events related to disease in plant populations. Artificial neural networks (ANNs) are said to excel at extracting sometimes subtle patterns from large multivariate data sets without making assumptions about model form because of poorly understood, potentially complex relationships [17]-[19]. As a result, ANNs have been reported to be a good alternative to conventional multiple regression techniques. The following significant development involved an ANN's feedback function, which changed weights to correspond to minimal error values. However, it wasn't until the 1980s that ANNs gained widespread acceptance as a class of models when the activation threshold was changed to a continuous function and a multilayer network began taking derivatives from a backpropagation of errors to approximate the target output by nonlinear functions [20]. The generalised regression neural network, a one-pass learning algorithm with a highly parallel structure that provides estimates of continuous variables and converges to the underlying (linear or nonlinear) regression surface, is another option to back-propagation, which has been widely used in regression problems. The generalised regression neural network (GRNN) and backpropagation neural network (BPNN) designs have both remained mainstays among the ANN family of models.

Both of these ANN designs, nevertheless, have their own drawbacks. Backpropagation has the drawback that it may need several iterations to get the desired outcome. In addition, rather than locating the global least error surface, it is vulnerable to convergent to local minima. The lengthy training period could be necessary for an advanced application. Because it learns quickly and has the capacity to converge to the ideal regression surface when the number of data increases significantly, the BPNN may be used as a safeguard against being caught in local minima [21]. To analyse new points, however, GRNN also needs a significant amount of processing. It tends to be huge and sluggish, yet trains fairly instantly. As a result of its incapability to extrapolate, or project a function beyond the range of known data points, GRNN is likewise unable to forecast the value of unknown data points [22]. Therefore, there is a pressing need to take use of the newest and future prediction softwares for a better and enhanced knowledge of the interactions between plants, pathogens, and environments.

3. Proposed Works

The proposed Optimized DRL approach has three major steps such as Preprocessing, Feature Learning and Classification. The flow of proposed work is depicted in figure.1.

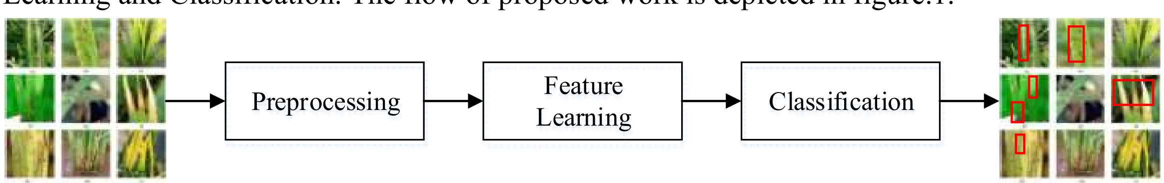

Fig.1 Flow of proposed DRL approach

3.1. Preprocessing

Data augmentation is the process of expanding the dataset to improve the performance of the model by producing various types of pictures. It is also helpful in reducing the model's overfitting issue during the training phase. Instead of the underlying connection, the overfitting issue arises when random noise or mistakes are present. Since some irrelevant patterns could appear when the model is being trained, extra images were created from each image with the aid of data augmentation. Several approaches, including rotation transformations, horizontal and vertical flips, and intensity disturbances, which includes brightness disturbances, were employed for data augmentation activities. In a Gaussian noise processing technique, the natural sources, such as thermal, are in charge of producing the noise. It is important to note that Gaussian noise disrupts the grey values in digital photographs. For improved outcomes, Gaussian noise pictures were utilised to train the model using the training data set. The pictures in both the training set and the testing set are each 300 by 300 pixels in size. To increase the dataset to 5000 total pictures, image augmentation techniques including rotation, left/right flipping, and skew were used. The photos have been downsized to 224x224 or 299x299 pixels (depending on the models used). Each picture pixel value is rescaled to a value between [0-1] for floats or [0-255] for integers. Ratios of 60:40 have been applied to the dataset. Each class of rice disease contains 1000 photos in the training set. There are 2000 total photos in the testing set.

3.2. Feature Selection

ABO is an effort to imitate the alert "maaa" noises pushing the buffalos to remain on to exploit and alarm "waaa" sounds urging the buffalos to go on to explore behaviour of African buffalos in its foraging tasks. The buffaloes can tailor their hunt for food sources thanks to these noises. The ABO is a population-based algorithm where individual buffalos cooperate to find a solution to a specific issue. A solution in the search space is represented by each buffalo in the ABO algorithm.

3.2.1. The Basic Flow of the ABO

The population of buffalos is initialised using the algorithm first. This is accomplished by giving each buffalo a random position inside the N-dimensional space. The fitness of each buffalo inside the search area is then updated. The position vector for that specific buffalo is saved if the fitness is higher than the maximum fitness of that particular buffalo (bpmax). The herd's maximum (bgmax) is saved if the fitness is higher than the herd's overall maximum. The finest buffalo is checked to see whether it is updating last. In the event that it is updating, it then checks the halting conditions. At this stage, if our global best fitness satisfies our exit criterion, the run is over and the location vector is presented as the answer to the problem at hand. In Figure 2, the ABO algorithm is displayed.

Step1. Objective function $f(x)$ $x=(x1, x2, \ldots\ldots\ldots xn)^T$

Step2. Initialization: randomly place buffalostonodes at the solution space;

Step3. Update the buffalos fitness values using Equation (1)

$$w._k+1 = w._k + lpr_1(bg_{maxt.k} - m._k) + lpr_2(bp_{max.k} - m._k) \quad (1)$$

where $w._k$ and $m._k$ represents the exploration and exploitation moves respectively of the k^{th} buffalo (k=1,2,………..N) ; lp_1 and lp_2 are learning factors; r_1 and r_2 are random numbers between [0,1];

bg_{max} is the herd's best fitness and bp_{max} , the individual buffalo's best

Step4. Update the location of buffalo k in relation to $bp_{max.k}$ and $bg_{max.k}$ using (2)

$$m._k+1 = \lambda (w._k + m._k). \quad (2)$$

λ is a unit of time

Is bg_{max} updating. Yes, go to 6. No, go to 2

Step5. If the stopping criteria is not met, go back to algorithm step 3

Step6. Output best solution.

Figure 2. ABO algorithm

With reference to Figure 2, it should be noted that the movement equation of the method includes three components: the first, w.k, stands for the buffalo's recollection of its previous location. Each buffalo has a memory that has a list of alternatives to the current local maximum location. There is a chance that the buffalo will select from the target list of potential answers rather than the highest point of the current herd. The third portion, lp2r2(bpmax.k - m.k), denotes the intelligence of the buffalos. The second part, lp1r1(bgmaxt.k - m.k), is concerned with the cooperative part of the buffalos and is a pointer to the buffalo's social and information-sharing experience. Therefore, the ABO draws on the buffaloes' memory, intelligence, and compassion to come up with solutions.

3.2.2. Buffalo Movement

Within the solution space, the movement of buffalos is governed by two major equations. Equations (1) and (2) (see image 1) describe them. The herd's precise speed-based movement is described by the movement equation (1). Given the two opposing pressures (bpmax and bgmax), movement adjustment is provided by the maaa update (stay on to exploit) equation (2). The default setting for the parameter, which specifies the discrete time period across which the buffalo must travel, is 1.0. The outcome is that the animal has a new home.

The global maximum position and the personal maximum position, which both define the representative influence on the animal's decisions, are the two main components of the second equation. In order to ask the animal to exploit, the method subtracts the maaa element (m.k) from the maximum vector. It then multiplies this result by a random integer (r1, r2), which is typically between 0.0 and 0.6, and a learning factor (lp1, lp2) to account for learning. Further research is being done to acquire numbers that could produce better results, although using random values between 0.0 and 0.6 has so far shown to be useful in generating quick convergence. The total of these items is then added to the waaa element (inviting the animals to continue exploring) for the specific sector dimension. In order to assist the animals navigate around the problem space, it should be emphasised that the random numbers provide a certain level of unpredictability in the path. As the algorithm advances, it does this by placing a greater or lesser focus on the global or personal maximum solutions depending on the need for more exploration or exploitation, respectively.

3.3. Classification by Deep Learning

RL is a part of machine learning. It involves doing the proper action to increase the reward in specific states. It is utilised by a range of software applications, devices, and tools to determine the best course of action in a given situation. RL makes use of learning data that already have the answer, in contrast to supervised learning. As a result, in supervised learning, the model is educated on the right answer, but in reinforcement learning (RL), the reinforcement agent chooses how to perform a given task. Learning is performed by experience without a dataset. The essential RL tenet is that the input must represent the beginning state from which the models start. The output has a wide range of potential results since different problems are approached from different angles. Depending on the input, the model will return the value of the state, and the user will decide whether to penalise or reward the model based on its output. As the model continues to learn, the best solutions are selected based on the highest reward. In real-world learning (RL), an agent interacts with an environment and decides the optimal course of action depending on the circumstances. The environment creates the ensuing state and rewards it when an agent does an action that was derived from another policy. Model-free RL techniques like SARSA and Q-learning are often used. Their exploration policies do not differ from their exploitation policies. While Q-learning is an off-policy tactic where the agent learns based on the action by another policy, SARSA is an on-policy approach where learning is based on the current action of the current policy. The efficiency of RL has been shown in resource allocation, cloud computing, and compute offloading, among other applications. The policy predicts the following(s, a) based on the current a state-action(s, a). To do this, we use temporal-difference (TD), which enables the agent to switch between pairs of states and actions while changing the rule that is applied at each timestamp. To address challenging, significant state-space issues, the deep SARSA function is revised as follows:

$$Q(S_t, A_t) = R(S_t, A_t) + \gamma Q(S_{t+1}, A_{t+1}) \qquad (14)$$

where $Q(S_t, A_t)$ is the value of Q for the action A in system state S at time $t, R(S_t, A_t)$ is the reward when the agent selects the action A_t at state S_t, and γ denotes the discount factor; the epsilon-greedy policy is used to select the best action A_{t+1} in the current state S_{t+1}.

Many traditional reinforcement learning methods have been used for computation offloading. For difficult video games, for instance, RL techniques were used, and different RL approaches, such as actor-critic, SARSA, Q, and R learning, were contrasted. The SARSA outperforms other RL algorithms because of its bigger rewards.

Markov decision processes (MDPs) are used in RL to effectively increase the reward in the training task of an agent interacting with the environment. Therefore, the future reward at time t is described as,

$$R_t = \sum_{k=0}^{T} \alpha^k r_{t+k+1} \qquad (15)$$

where $\alpha \in (0,1]$ is a discount factor, and r_t is the reward when action a is taken at time t. When the agent takes the action a under the policy π in state S at the time t, denoted by $Q^\pi(s, a)$. Thus,

$$\begin{aligned} Q^\pi(s,a) &= E_\pi\{R(t) \mid s_t = \mathrm{s}, \quad a_t = a\} \\ &= E_\pi\{\textstyle\sum_{k=0}^{\infty} \alpha^k r_{t+k+1} \mid s_t = \mathrm{s}, \quad a_t = a\} \end{aligned} \qquad (16)$$

where the expected reward is and the policy function for the action A_t is. The goals of the training assignment are to maximise rewards and realise Q's (s,a) ideal state and behaviour. There are two methods in RL. Both are referred to as SARSA and Q-learning, respectively. We will use SARSA in this inquiry because it has been demonstrated that it can select a secure route. This is considered acceptable in the current study, which is focused with selecting an optimum and safe method for moving difficult tasks to the edge cloud. SARSA is an on-policy technique, which means that the outcome is based on the value of the present state (s_t) and the present action (a_t). The following formula can be used to change status and action values,

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma Q(s^*, a^*) - Q(s,a)] \qquad (17)$$

In SARSA learning, the training task is a quinary (s, a,r,s ∗ , a ∗), which is updated sequentially.

4. Experimental Results

This part presents the experimental analysis and CPRF algorithm accuracy. We first present the chosen datasets and go over the experimental strategy. The original agricultural data are then gathered from actual farms and employed in a number of algorithms based on a number of parameters that affect the production of agricultural goods. In the meanwhile, we contrast CPRF with alternative approaches. Finally, several algorithms' categorization accuracy is reviewed. We get the conclusion that CPRF is the best algorithm based on accuracy. Crop yields are significantly impacted by plant diseases and insect pests, and a site that is badly damaged by diseases frequently has no harvest or a very small harvest. As a result, we initially investigate three prevalent rice illnesses. Four random forest algorithms are used to anticipate, analyse, and compare the data from the afflicted region through the gathering and analysis of data, such as images of damaged leaves. The findings are displayed using graphs.

4.1. Dataset Description

Datasets gathered by agricultural researchers from each year's official statistician were utilised as the foundation for the proposed algorithm's validation and comparison with an earlier decision tree predictor. There were 18 datasets gathered. The first 17 of these datasets were used for testing or training, while the last dataset served as an independent validation dataset. The HuNan Province in China, a regional agriculture agency, gathered and organised the independent validation dataset. Two features of the validation dataset were applied in order to verify the precision and effectiveness of the CPRF algorithm. In the first, the temperature of rice fields was mostly documented over a period of more than 15 years, and in the second, the precipitation and insects that have impacted rice output over the same period were primarily reported. The statistics of the agricultural datasets are listed in Table 1.

Table 1. Compositions of training datasets and aspects of the validation dataset.

Training Dataset			**Agricultural Validation Dataset**		
Name	**No. of Diseases**	**(numMin, numMaj)**	**Name**	**No. of Sequences**	**(numMin, numMaj)**
Train-dxs	19,550	(5619, 30,709)	Ytest95	95	(1938, 16,319)
			RYtestset219	219	(6098, 21,996)

4.2. Comparative Analysis

The findings demonstrate that, under the identical circumstances, RBD's forecast accuracy is greater when utilising microclimate data than when using air climate information. The performance of the atmospheric climate feature sets was compared first. We discovered that the feature set that includes relative humidity information outperforms the feature set that does not, proving that relative humidity plays a substantial role in RBD prediction. The second discovery is that the RBD prediction will be more accurate if we include microclimate data and atmospheric climate features in our learning model. The observation period is then the subject of studies to examine if the forecast outcome will be affected.

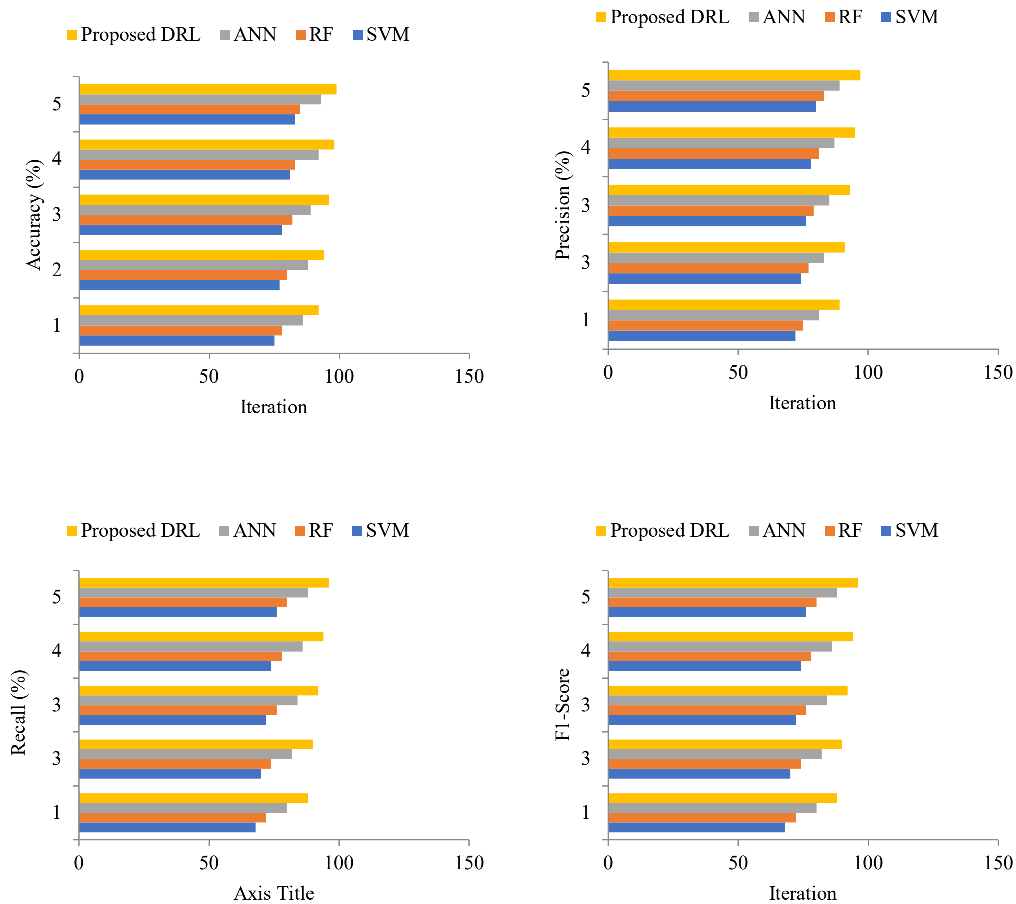

Fig.3 Comparative Analysis on Accuracy, Recall, Precision, F-1 Score

We assume that N, a number between 1 and 5, is the chosen number of observation periods. Testing which parameter works better is what we want to do. We may identify a better setting for N based on the experimental findings in fig.3. When the value of N is set to 2, it is shown that the neural network model has a classification accuracy of 96.6% and a recall of 93.8%. Although the accuracy rate is the greatest of all neural network classification models, the recall rate is a little lower than when N = 3. If N equals 2, the accuracy and recall for the proposed model are 97.4% and 94.5%, respectively.That means increase in iteration will improve the classification results. We intend to expand the number of target diseases and the range of symptoms for each condition in order to make our system more useful in the future. We also intend to create a server upkeep system that can quickly manage additional users and LINE groups without the need for specialised database or LINE Bot technical expertise. In order to enhance the system's illness detection performance, we also want to develop a self-refinement detection model utilising the experts' comments on incorrect detection.

5. Conclusion

Protecting rice plants has been a top priority for agricultural specialists. However, a comprehensive examination of the plant disease problem has not been done. To prevent the disease's severe negative effects on crop productivity, it is crucial to correctly identify rice infections. However, the present approaches of disease diagnosis in rice are neither accurate nor efficient, and occasionally further tools are required. In order to preserve the healthy and regular growth of the rice plants, it is imperative to identify any sickness early on and before the damaged plants receive the required treatment. Given the time and effort required for manual sickness detection, having an automated solution makes sense. In this paper, a machine learning-based technique for identifying illnesses in rice leaves is described. Three of the most common diseases impacting rice plants are leaf smut, bacterial leaf blight, and brown spot disorders, according to this research. Clear images of broken rice leaves over a white background made up the input. We suggested an Optimised Deep Reinforcement Learning (Optimised DRL) method to address this. After the proper pre-processing, the African Buffalo Optimisation (ABO) algorithm performs feature learning. Deep SARSA algorithm is utilised for categorization using the best characteristics. The decision tree technique generated outcomes on the test dataset with an accuracy of above 97% after 10-fold cross-validation.

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