Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Issue 8, No.4, August : 2024

ENHANCED CNN MODEL FOR DETECTING RICE PLANT DISEASES: ADVANCING DEEP LEARNING APPLICATIONS IN AGRICULTURE.

Varsha Masulker, M. Tech Scholar, Department of Computer Science Engineering, Technocrates Institute of Technology, Bhopal, MP. Email: vpmasulker@gmail.com
Dr. Bhupendra Verma, Associate professor, Department of Computer Science Engineering, Technocrates Institute of Technology, Bhopal, MP
Dr. Manoj tyagi, Head of Department, Department of Computer Science Engineering, Technocrates Institute of Technology, Bhopal, MP

Abstract *Global economic development and food security are greatly influenced by agriculture, and rice is a major crop that is particularly vulnerable to diseases that reduce its quality and output. It is important to identify diseases promptly and accurately in order to minimize these losses. Promising approaches to improve disease detection in rice plants are provided by recent developments in deep learning, particularly Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Recurrent Neural Networks (RNNs). When it comes to recognizing visual cues that may indicate a variety of illnesses, CNNs are particularly good at extracting spatial characteristics from leaf pictures. In the meanwhile, temporal relationships are captured by LSTM and RNNs, which is crucial for modelling the evolution of diseases and forecasting epidemics. Their architectural layouts, essential parts, dependency management, training difficulties, and deployment situations are all examined in this comparative analysis. While LSTM and RNNs are skilled at managing sequential data, they require careful parameter adjustment to maximize performance. CNNs, on the other hand, are efficient in image-based applications but demand more CPU resources. This study intends to assist researchers and agricultural practitioners in choosing and implementing suitable deep learning techniques for efficient management of rice plant diseases, ultimately promoting sustainable agricultural practices and global food security. To that end, it highlights these strengths and limitations.*

Keywords: *Agriculture, Rice plant diseases, deep learning, Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, Recurrent Neural Networks (RNNs)*

I. INTRODUCTION

Infrastructure, trade, employment, food supply, and other aspects of economic growth have all been facilitated by agriculture in both developed and developing nations. Agriculture accounts for a significant portion of the GDP (Gross Domestic Product) in some developing nations. Certain African nations don't even allocate a portion of their public budget to agriculture, which therefore doesn't boost their GDP. The majority of those living in poverty labor in the agriculture industry to make ends meet. This industry employs over 78% of the world's impoverished, providing jobs for workers, herders, smallholders, etc. The source of the food supply is agriculture. The demand for food has increased dramatically as a result of population growth. Agriculture's correct and ongoing upkeep of the food supply chain will undoubtedly contribute to the economic prosperity of any nation. For the importing nations, the price growth of agricultural goods is a burden. The intense rivalry amongst exporters is the cause of the variations in export prices that are seen [1].

In many nations across the world, agriculture is the main source of revenue. Farmers choose their crops, paddies, and associated pesticides based on the value of agriculture and the desire to maximize plant development within a finite amount of time. The primary food crop in a number of nations is rice. Diseases that impact crop quality and quantity are causing serious issues for rice plants in the agriculture industry these days. The many causes of the reduced output rate include a lack of sufficient professional availability in the farming field, ignorance of diseases and pests, and poor understanding of fertilizer management [2].

Plant diseases are thought to be the cause of 13% of the loss in agricultural output worldwide. The above statistics emphasize how crucial it is to diagnose plant illnesses in order to reduce production losses. But before anything else, it's important to know what causes plant illnesses. Plant disease production is facilitated by three factors: the pathogen, the host, and a conducive environment. The triangle depicting plant disease in Figure 1 is the result of these variables. Most diseases start off small and work their way up the plant to harm it. Following infection, several plant diseases disseminate throughout the crop. Crops must thus be routinely observed as prompt disease treatment will aid in halting its spread. Following pollination, plant diseases also often show up later in the growing season. Specifically, up to 50% of yield losses are caused by fungal infections. Consequently, the majority of current research employs deep learning, computer vision, and machine learning algorithms to diagnose illnesses from photos of plant leaves. An accurate diagnosis of plant diseases should include early-season identification of the disease, identification of multiple diseases in different crops and multiple simultaneous diseases, estimation of the disease's severity, estimation of the quantity of pesticide that should be applied, and practical measures to control the disease to prevent its spread [3].

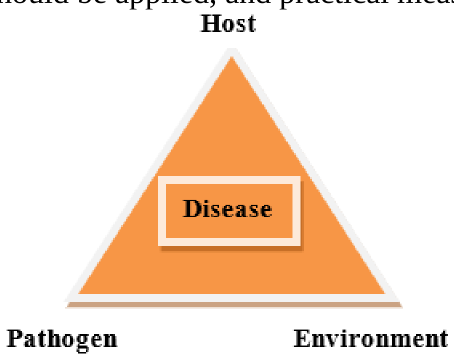

Figure 1: Plant Disease Triangle [3]

The plant disease triangle in figure 1 shows that all three elements—a virulent pathogen, a vulnerable host, and a permissive environment—must coexist and interact favorably for a disease to manifest. The sickness is unlikely to occur if any one of these elements is absent or inconvenient. Comprehending this interplay facilitates the development of efficacious disease mitigation tactics, including crop varieties with resistance, appropriate farming methods, and alterations to the surroundings.

There are four main categories of illnesses that affect rice plants: disorders, bacterial diseases, fungal diseases, and viral diseases. Bacterial blight, pecky rice, grain rot, and foot rot are examples of bacterial illnesses. Brown spots, black horse riding, leaf blast, false smut, and other conditions are examples of fungal infections. A few viral illnesses are rice tango, green rice stunt, and rice yellow mottling. Among the several illnesses that affect rice plants are alkalinity, bronze, white tip, cold damage, and others. The first is fungal/bacterial assault, and the second is unexpected climate shift. These are the two main causes of rice plant illness. There are a few key factors we must take into account while managing rice diseases, including accurate data gathering, appropriate plant monitoring, and many more. One crucial and significant step is gathering samples from the sick rice plant. Multimedia sensors can be installed at various agricultural areas to do this. This facilitates routinely checking on the rice plant. Furthermore, records and investigations may be made about the effects of climate change on rice plants. However, there are some drawbacks to this method as well, such as the need for routine system maintenance and low precision caused by shadows in the photos that are taken [4].

The given table provides a concise overview of common rice plant diseases, highlighting their causes, symptoms, and effective management strategies.

Table 1: Common Rice Plant Diseases

Disease	Cause (Pathogen)	Symptoms	Management Strategies
Blast	Fungus (Magnaporthe oryzae)	Leaf lesions, wilting, necrosis	Resistant varieties, proper field sanitation, fungicides
Bacterial Blight	Bacteria (Xanthomonas oryzae)	Yellowing, wilting, lesions on leaves	Resistant varieties, copper-based bactericides, field hygiene
Sheath Blight	Fungus (Rhizoctonia solani)	Lesions on leaf sheaths, stunted growth	Proper water management, fungicides, resistant varieties
Brown Spot	Fungus (Bipolaris oryzae)	Brown lesions on leaves, reduced grain yield	Use of balanced fertilizers, fungicides, resistant varieties
Tungro	Virus (Rice tungro bacilliform)	Stunted growth, yellow-orange discoloration	Plant resistant varieties, control of vector (green leafhopper)
False Smut	Fungus (Ustilaginoidea virens)	Greenish spore balls on grains	Seed treatment, proper field sanitation, resistant varieties
Leaf Scald	Fungus (Microdochium oryzae)	Large brown spots on leaves, leaf drying	Resistant varieties, fungicides, crop rotation
Narrow Brown Leaf Spot	Fungus (Cercospora janseana)	Narrow brown lesions on leaves	Resistant varieties, proper field management, fungicides
Rice Blast (Panicle Blast)	Fungus (Magnaporthe oryzae)	Lesions on panicles, grain rot	Resistant varieties, field sanitation, fungicides
Grain Discoloration	Fungi/Bacteria (various)	Discolored grains, reduced grain quality	Proper drying and storage, fungicides, resistant varieties
Disease	Cause (Pathogen)	Symptoms	Management Strategies

II. DEEP LEARNING TECHNIQUES FOR THE DETECTION OF RICE PLANT DISEASE

Deep Learning was developed to help neurons behave or think like people. To predict the required results, DL was developed using a multineural network architecture with several convolution layers. A variety of network topologies, from the most basic to the most intricate, are included in DL. Beginning in the early 1940s, deep learning emerged as a subclass of machine learning (ML), coinciding with the development of "threshold logic." It has been used to computer simulations that have been shown to closely mimic human biological processes. Technological developments may enable farmers to identify rice illnesses, which would be a very practical way to address these issues. Deep Learning technologies are currently the subject of several investigations aimed at diagnosing similar illnesses. While some research developed their own methods to address this problem, others used deep learning principles and methodologies. Few research have been done on diagnosing diseases in rice plants, compared to the large body of research on identifying ailments in other plants like tomatoes and peaches [5].

Early detection and prompt, correct diagnosis are the keys to effective illness management. Initially, a manual inspection was the sole method to determine whether a plant leaf was diseased based merely on its texture. Professionals with expertise and experience were required for the task, which required patience and decreased agricultural yield. Crop disease identification and detection has been accomplished through the application of deep learning techniques. Citrus tree fruit estimates are made by Dorj et al. using image processing techniques, Bai et al. cluster features using neighborhood gray scale approach to extract the disease area of cucumber leaves, and Ma et al. extract the video's important frames using mean pixels value method. Furthermore, several approaches to recognition and detection have been tried, including deep learning-based feature extraction and picture segmentation of crop diseases [6]. A significant impact of deep learning (DL) is being seen on computer vision-based characteristics, such as illness diagnosis and identification. DL can forecast a disease or an item using sample or training data. DL usually operates with large amounts of data. Training large and complex data models can be expensive. Substantial amounts of hardware are also needed to carry out complex mathematical calculations. Conversely, a multi ensemble model, which includes Long Short Term Memory Networks (LSTMs), Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs), is a single model composed of many classification models. Predicting outcomes more accurately than individual models is the primary advantage of a multi-model ensemble model. When a dataset contains both linear and nonlinear data, ensemble techniques are advantageous because they let several models collaborate to handle the various data kinds.

A. Convolutional neural networks

The application of convolutional neural networks (CNNs) has increased recently. A CNN consists of an input layer, a final output layer, and several more hidden layers. The most prevalent kinds of hidden layers in a CNN are convolutional layers, fully connected layers, normalisation layers, and pooling layers. More layers might be employed for models that are more complex. CNN architecture has shown to be an excellent solution for a variety of computer vision and machine learning problems. The training and prediction specifics of CNN are reserved for later parts. This CNN model is commonly used in modern Machine Learning applications due to its exceptional performance, setting new records. Linear algebra serves as the foundation for these CNNs. Matrix vector multiplication is the representation used for data and weights [7].

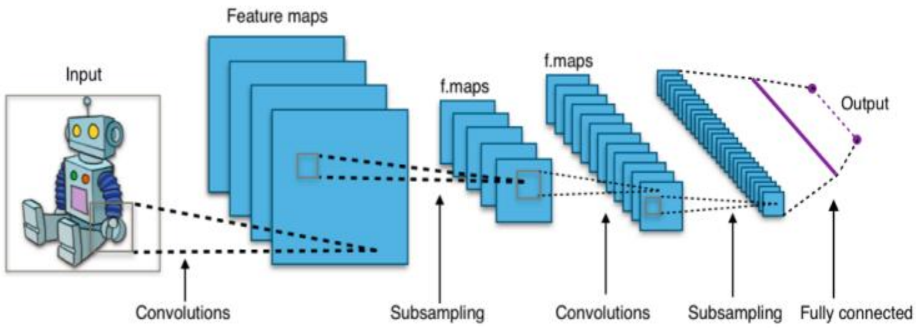

Figure 2: A typical CNN architecture [8]

The architecture of a convolutional neural network (CNN) is shown in Figure 2. It illustrates how an image is input, processed via several layers of convolutions and subsampling, advanced to fully connected layers, and ultimately outputted.

B. Long Short-Term Memory

Recurrent Neural Networks (RNN) include an improved version called Long Short-Term Memory (LSTM) that solves the problem of capturing long-term dependencies. After being first presented in 1997 and then improved upon in 2013, LSTM became widely known in the deep learning world. The LSTM network is a unique kind of RNN. The LSTM network is able to handle the correlation within time series across the short and long terms by considering the hidden layer as a memory unit [9]. LSTM models have demonstrated superior efficacy in preserving and using information across extended sequences when compared to typical RNNs. An LSTM network works by feeding its unit the current input at a given time step as well as the output from the previous time step. The LSTM unit then produces an output that is transmitted to the next time step. For categorization, the last hidden layer of the previous time step—and occasionally all hidden layers—are frequently used. The input, forget, and output gates are the three gates that make up an LSTM. Every gate controls the information flow in a certain way. Based on the current input and the prior internal state, the input gate determines how to update the internal state. How much of the prior internal state should be lost is decided by the forget gate. Lastly, the output gate controls how much the internal state affects the system [10].

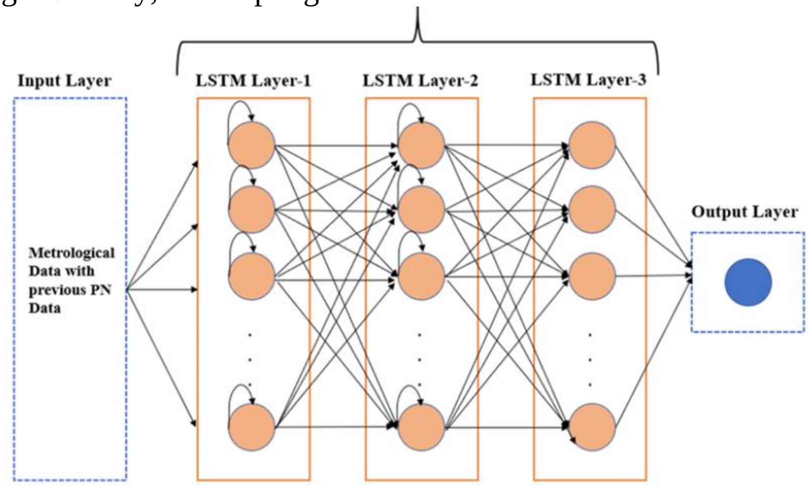

Figure 3: LSTM Model Architecture [11]

A Long Short-Term Memory (LSTM) network architecture is shown in Figure 3, where the input is a combination of historical power network (PN) data and meteorological data. Three LSTM layers—each with recurrent connections and interconnectedness—process the data before reaching an output layer.

C. Recurrent neural networks

Recently, RNNs have proven to perform promisingly on a range of natural language processing tasks and have yielded better outcomes on several tasks, including language translation, sentiment classification, and picture captioning. There are several scenarios when the data sequences characterise the case. In a language modelling job, for instance, a word's meaning is defined by its sequence. Information is illogical if the sequences are broken. The underlying presumption of a typical neural network is that there is no dependence between input and output [12]. In this instance, in order to properly understand the data, a network linking to earlier information is required. RNNs, so named because they do the identical calculation for every sequence element, are helpful in responding. Every state's outcome is reliant on the preceding computation. RNNs maintain a "memory" that contains the data about the computations that have already been made [13].

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Issue 8, No.4, August : 2024

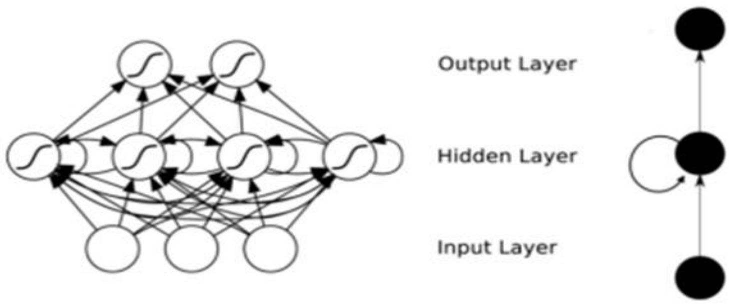

Figure 4: Architecture of RNN Model [14]

An input layer, a hidden layer, and an output layer make up the three layers of a basic feed-forward neural network shown in Figure 4. With arrows denoting the direction of data flow from the input to the output, each layer's neurons are fully coupled to those in the layer below it.

III. Comparative Analysis of different models

Convolutional neural networks (CNNs), long short-term memory (LSTM) networks, and recurrent neural networks (RNNs) are the three types of neural networks that are compared in the table below. The neural networks are compared in each row of the table according to distinct criteria, including main usage, architecture, essential components, managing dependencies, memory mechanism, training difficulty, typical use cases, advantages, disadvantages, examples, and training data needs.

Table 2: Comparative Overview of Deep Learning Networks

Features	**Convolutional Neural Networks (CNNs)**	**Long Short-Term Memory (LSTM) Networks**	**Recurrent Neural Networks (RNNs)**
Primary Application	Computer vision, image processing	Sequence prediction, time series forecasting, natural language processing	Time series analysis, sequence data processing, and natural language processing
Architecture	Includes several hidden layers, such as pooling and convolutional layers, in addition to the input and output layers.	Consists of three gates in the LSTM cells: input, forget, and output. It also includes an input layer and an output layer.	Consists of hidden layers, output layers, and input layers with recurrent connections between each neuron.
Key Components	Convolutional layers, pooling layers, fully connected layers, normalization layers	Input gate, forget gate, output gate, cell state, and hidden state	Recurrent connections, hidden state
Handling of Dependencies	Processes data in a hierarchical manner, capturing spatial dependencies	Specifically designed to capture long-term dependencies and address vanishing gradient problems	Captures sequential dependencies but struggles with long-term dependencies due to vanishing/exploding gradients
Memory Mechanism	No explicit memory mechanism; uses hierarchical feature extraction	Utilizes cell state and gates to retain information over long sequences	Utilizes hidden state to retain information from previous time steps

Training Complexity	Requires large datasets and significant computational resources	Requires specialized training techniques and can be computationally intensive	Easier to train compared to LSTM but still faces challenges with long sequences
Common Use Cases	Image classification, object detection, image segmentation, video analysis	Language modeling, speech recognition, time series forecasting, text generation	Language translation, sentiment analysis, image captioning, speech recognition
Strengths	Excellent at capturing spatial hierarchies, high performance in image-related tasks	Effective at capturing long-term dependencies, robust to vanishing gradient problem	Good at capturing short-term dependencies, suitable for sequence prediction tasks
Weaknesses	Restricted capacity to manage sequential data; unfit for work involving temporal dependencies	More complex architecture, higher computational cost, longer training times	Struggles with long-term dependencies, prone to vanishing/exploding gradient problems
Examples	AlexNet, VGGNet, ResNet, Inception	LSTM-based models for language translation (e.g., Google Translate), speech recognition (e.g., Siri), and text generation (e.g., GPT)	Traditional RNNs, Simple RNNs, GRUs (Gated Recurrent Units)
Training Data Requirements	Large labeled datasets, particularly for image-related tasks	Large datasets with sequential data, particularly for text and time series tasks	Requires sequential data, but can work with smaller datasets compared to CNNs and LSTMs

IV.Conclusion

In crops like rice, efficient disease control is essential due to the economic importance of the agricultural industry. Rice plant diseases may be identified and managed with more precision techniques including CNNs, LSTM networks, and RNNs. Detecting visual indicators of plant diseases is a good use for CNNs as they perform well on spatial analysis tasks like object detection and picture classification. LSTM networks operate well in tasks like time series forecasting and natural language processing, which makes them useful for sequential data analysis. This is because they can capture long-term dependencies. Recurrent neural networks (RNNs) are useful for sentiment analysis and language translation, but they have difficulties with long-term sequences. The comparative analysis reveals that every model has unique benefits and drawbacks. While LSTM networks efficiently handle long-term dependencies but are computationally demanding, CNNs are better at tasks involving images but need large datasets and computational power. RNNs, on the other hand, are simpler to train but have difficulty with long-term sequences. The choice of a deep learning model for rice plant disease detection depends on the individual job constraints, such as data type and relationships. Future research should focus on combining different deep learning algorithms to better the accuracy and efficiency of disease detection systems, ultimately contributing to enhanced agricultural output and economic development.

REFERENCES

[1]Sharma, M., Kumar, C. J., & Deka, A. (2022). Early diagnosis of rice plant disease using machine learning techniques. Archives of Phytopathology and Plant Protection, 55(3), 259-283.
[2]Daniya, T., & Vigneshwari, S. (2019). A review on machine learning techniques for rice plant disease detection in agricultural research. system, 28(13), 49-62.

[3]Ahmad, A., Saraswat, D., & El Gamal, A. (2023). A survey on using deep learning techniques for plant disease diagnosis and recommendations for development of appropriate tools. Smart Agricultural Technology, 3, 100083.
[4]Tawde, T., Deshmukh, K., Verekar, L., Reddy, A., Aswale, S., & Shetgaonkar, P. (2021). Rice plant disease detection and classification techniques: a survey. Int. J. Eng. Res. Technol., 10(7), 560-567.
[5]Udayananda, G. K. V. L., Shyalika, C., & Kumara, P. P. N. V. (2022). Rice plant disease diagnosing using machine learning techniques: a comprehensive review. SN Applied Sciences, 4(11), 311.
[6]Li, D., Wang, R., Xie, C., Liu, L., Zhang, J., Li, R., ... & Liu, W. (2020). A recognition method for rice plant diseases and pests video detection based on deep convolutional neural network. *Sensors*, *20*(3), 578.
[7]Shovon, M. S. H., Mozumder, S. J., Pal, O. K., Mridha, M. F., Asai, N., & Shin, J. (2023). Plantdet: A robust multi-model ensemble method based on deep learning for plant disease detection. IEEE Access, 11, 34846-34859.
[8]Purbasari, I. Y., Rahmat, B., & Pn, C. P. (2021, May). Detection of rice plant diseases using convolutional neural network. In IOP Conference Series: Materials Science and Engineering (Vol. 1125, No. 1, p. 012021). IOP Publishing.
[9]Zhao, Z., Chen, W., Wu, X., Chen, P. C., & Liu, J. (2017). LSTM network: a deep learning approach for short-term traffic forecast. IET intelligent transport systems, 11(2), 68-75.
[10] Shiri, F. M., Perumal, T., Mustapha, N., & Mohamed, R. (2023). A comprehensive overview and comparative analysis on deep learning models: CNN, RNN, LSTM, GRU. arXiv preprint arXiv:2305.17473.
[11] Surakhi, O., Zaidan, M. A., Fung, P. L., Hossein Motlagh, N., Serhan, S., AlKhanafseh, M., & Hussein, T. (2021). Time-lag selection for time-series forecasting using neural network and heuristic algorithm. Electronics, 10(20), 2518.
[12] Ahmed, S. F., Alam, M. S. B., Hassan, M., Rozbu, M. R., Ishtiak, T., Rafa, N., ... & Gandomi, A. H. (2023). Deep learning modelling techniques: current progress, applications, advantages, and challenges. Artificial Intelligence Review, 56(11), 13521-13617.
[13] M. Sheikhan, Z. Jadidi, and A. Farrokhi, ‘‘Intrusion detection using reduced-size RNN based on feature grouping,’’ Neural Comput. Appl., vol. 21, no. 6, pp. 1185–1190, Sep. 2012.
[14] Yin, C., Zhu, Y., Fei, J., & He, X. (2017). A deep learning approach for intrusion detection using recurrent neural networks. Ieee Access, 5, 21954-21961.