Frontiers in Health Informatics
ISSN-Online: 2676-7104
www.healthinformaticsjournal.com
2024; Vol 13: Issue 3
Open Access

# Evaluating The Efficiency of RNN Model for Real Time Fruit Disease Detection

**Dr. Deepali Patil[1], Dr. Sonali Patil[2], Dr. Swati Khawate[3], Mrs. Akanksha Goel[4], Dr. Manisha Bhende[5]**

[1] Dr. D. Y. Patil School of Science and Technology, Dr. D. Y. Patil, Vidyapeeth, Pune, Maharashtra, India. deepalipatil86@gmail.com

[2] Dr. D. Y. Patil School of Science and Technology, Dr. D. Y. Patil, Vidyapeeth, Pune, Maharashtra, India. - sonalipatil3011@gmail.com

[3] Ajeenkya D Y Patil School of Engineering, Pune, Maharashtra, India. khawate.swati@gmail.com

[4] Dr. D. Y. Patil School of Science and Technology, Dr. D. Y. Patil, Vidyapeeth, Pune, Maharashtra, India. akanksha.rkgit@gmail.com

[5] Dr. D. Y. Patil School of Science and Technology, Dr. D. Y. Patil, Vidyapeeth, Pune, Maharashtra, India. manisha.bhende@gmail.com

Cite this paper as: Deepali Patil ,Sonali Patil, Swati Khawate, Akanksha Goel, Manisha Bhende (2024) Evaluating The Efficiency of RNN Model for Real Time Fruit Disease Detection. *Frontiers in Health Informatics, 13* (3), 1545-1553.

**A B S T R A C T**

*Introduction: Fruit disease detection has been considered essential in maintaining nutrition security and productivity in agriculture in that respect the paper has presented a method that involves using RNNs in the automatic fruit disease classification they had gathered a phenomenal dataset of images of fruits and used it for training their regular RNN model these findings further turn out to be highly useful in characterizing the appearance of diseases in fruits and vegetables including that which causes contagious bacterial and viral infections RNN performs an incredibly good job of modeling sequential flavor image information which may be prime imperative for early detection these content generated within the appearance consider as opposed to other deep learning approaches it seems that RNN is an essential constraint in this task the discovery brought about by this research forms a rational approach toward transformation in agriculture and creating a difference in nutritional output*

***Keywords:*** *Recurrent Neural Networks, Deep learning, Food security, Fruit disease detection, Agricultural productivityIntroduction*

In the domain of agriculture especial in horticulture, disease diagnosis and control is one of the most crucial aspects in order to prevent food insecurity, to retain yield production and to avoid high loss in economies. Conventional approaches, on the one hand, involve the use of the naked eye by personnel who could end upikes concentrating on a particular area while missing others hence require so much time and resources. Diagnosis and control measures as required in agriculture, helps in the identification of diseases affecting the fruit crops, sustains the yield, decreases loss hence food security. Conventionally, disease diagnosis relies on visual assessments where experts conduct physical examinations – this is costly, time-consuming and riddled with inaccuracies. [1]

Recurrent Neural Networks (RNNs) which belongs to the family of deep learning models was created with a degree of accuracy. Tasks such as video analysis or image series processing excels at analyzing time-series data or sequences making them of a kind. In the context of agriculture, this competency can be very useful for tracking the advancement of plant diseases processes that may be rather delicate and gradual. [4] Using the RNNs the farmers can even learn the diseases existence before. RNNs are trained on large datasets of fruit images, allowing them to learn and identify minute changes that may indicate the onset of disease. [2] Unlike traditional models that treat each image independently, RNNs take into account the temporal aspect of the data, enabling them to capture dynamic changes over time. [3] Employing RNNs in fruit disease detection is their ability to automate the process, is one of the key advantage. This has the potential to increase both speed and accuracy in. [5] Automated systems powered by RNNs can continuously monitor crops, providing real-time alerts to farmers about the presence of diseases. [6] Such early detection is crucial for implementing timely interventions—such as targeted treatments or adjustments in cultivation practices—which can help prevent disease spread and minimize crop loss

To develop and test an operational real-time fruit disease detection system using Recurrent Neural Networks (RNNs) that can accurately detect various diseases of the fruits from the images [7]. Our goal has following main objectives

Design an Effective RNN-based Model: Application and execution of an architecture of RNN that could handle sequential image data and learn temporal patterns that are related to fruit disease.

Improve model performance: Achieves hyper-parameter tuning of the RNN model and some training techniques which would help in improving the accuracy and efficiency of the model for real-time applications.

Model accuracy testing: Verifying the capability of the model in detecting different fruit diseases correctly with the help of suitable metrics such as recall, precision, accuracy, F1-score, etc.

Capability for real time: By improving the computational efficiency of the model, enable fast detection of diseases and make it ready to use in practical agricultural applications.

Address Challenges: Identify and overcome potential challenges of data imbalance, class overlap, and robustness to variation in environmental conditions and image quality.

This research work is structured as per below mentioned points- 2 literature survey related to fruit disease detection 3 problem statement 4 methodology 5 results n discussion 6 conclusion.

**LITERATURE REVIEW**

The farming industry has big problems when it comes to keeping fruit plants healthy and productive. [8] It's very important to find fruit diseases quickly and correctly so that we can control them, avoid losing crops, and keep food in good condition. The old way of finding diseases usually involves people checking by hand, which takes a long time, can be biased, and often makes mistakes. New developments in computer vision and deep learning are now making it possible to find diseases automatically and more efficiently. [ 9]

One of the most effective methods for doing these two crucial tasks—image analysis and picture classification—is deep learning, a subset of machine learning. Convolutional neural networks (CNN) are primarily designed for static image data and cannot fully capture temporal changes in disease progression but are widely used in fruit disease detection has shown impressive performance in identifying disease-related visual patterns. On the other hand, for sequential data processing recurrent neural networks (RNNs) are ideal which is appropriate for modeling the time-series nature of disease development. [10] RNNs can capture the context and dependencies between successive frames of a video or image sequence. Make it easier to recognize subtle changes that point to illness.

Existing Research and Contributions

Many methods of fruit detection have been developed over the last few decades.

For that instance, proposed approach combines MTCNN with an improved augmentation technique to enhance detection performance. [12] In order to segment images of fruits and leaves of plants, a new hybrid intelligence algorithm called GAACO is presented in this study. GAACO divides images into discrete pixel sets efficiently by combining tabu list, ant colony optimization, and genetic algorithm approaches. Plant diseases are subsequently diagnosed by using the segmented images in conjunction with a support vector machine (TSVM).[13]

This study utilizes the YOLOv2 convolutional neural network to detect physiological diseases in tomato fruits. YOLOv2 is a fast and accurate object detection algorithm. To improve network performance, data augmentation techniques were used to increase the dataset size. The resulting model is capable of identifying both healthy and diseased tomato fruits. [14]

This paper introduces a mobile-based application that utilizes a convolutional neural network for the identification of pest and diseases on jackfruits as well as for the diagnosis of the extent of damage inflicted on the crop the algorithm used a collection of 2409 images for training the cnn achieved a score of more than 90 for the recognition of different patterns of damages that the application offers the diagnosis services in real-time and gives recommendations for fruit crop losses. [15]

This work provides a novel approach that combines support vector machines (SVM), artificial neural networks (ANN) and k-means clustering to detect fruit illnesses. The method makes use of the physical characteristics of fruits like their color texture and structural patterns to precisely identify fruits that are ill image segmentation is done using k-means feature extraction and classification is done with ANN and classification accuracy is further improved by SVM the suggested approach presents a viable way to enhance fruit disease diagnosis and maintain fruit output worldwide. [16]

In this article a convolutional neural network based computer vision system for recognition of the diseases affecting the guava crop is developed. The system is designed to identify deviant guava fruit early to reduce economic losses for farmers. The CNN model with the use of a dataset of guava image data with different diseases attained a high level of accuracy of 95. It has been estimated that the efficiency of the software ranges from 57; 61 yielded positive return. [17][23]

This study proposes a deep learning-based approach for detecting defects in citrus fruits using the Dense CNN algorithm. By incorporating data augmentation and preprocessing techniques, the proposed model achieves a significantly higher accuracy of 89.1% compared to a baseline model without these techniques. The results highlight the importance of data. [18]

This study offers a deep learning-based technique for diagnosing carrot diseases utilizing the inception v3 architecture. In order to detect and stop illnesses in apple fruit to prevent overfitting. The model is trained on a dataset of real and artificial carrot pictures. [19]

This study offers an iot-based technique for sick apple detection to find the most accurate model for identifying apple sickness. The system classifies images using deep learning methods various deep neural network configurations are tried. [20]

In order to detect fruit surface illnesses this research presents an enhanced mask r-cnn method. In order to improve feature integration and detection accuracy the algorithm uses a bottom-up horizontal connection approach by precisely identifying fruits from trees. [21]

This research aims to improve fruit output estimation mango fruit localization and detection in a dataset is accomplished using the u-net architecture which is intended for semantic segmentation. In order to improve fruit yield estimation accuracy, the study assesses how well u-networks. [22]

There are also several appealing areas which pose challenges with respect to the detection of real-time fruit diseases that are most efficient. Some of these limits depend directly on the accuracy, speed, and scalability of the detection system. Such limitations pose significant challenge to the system largely by the intended demand of providing high detection accuracy under diverse and variable real-world conditions. Some of these limitations include varying lighting, different types of fruit and many stages of disease of the same fruit type. Furthermore, it is important to note that real time processing is a task that is very computationally intensive and might be restrained by hardware limitations. These constraints can be avoided to a large extent by the use of Recurrent Neural Networks (RNN) that are known to work best with sequential data and temporal dependencies. The model can be constructed in a way that it utilizes RNNs with LSTM networks or GRUs allowing the disease patterns to be understood by the system over a period. Associating RNNs with advanced image preprocessing techniques, transfer learning, and model optimization strategies may contribute to real-time accuracy and performance thus evading this major limitation of environmental and computational factors. [3]

## PROBLEM STATEMENT

To the current problem, it is required to analyze the benefits that can stem from the use of Recurrent Neural Networks (RNNs) used for real-time detection of fruit disease, in reinforcing the issues of accuracy, speed and adaptability in ever-changing and diverse environments. Though technology has improved on imaging as well as artificial intelligence, the present-day applications mostly remain inefficient in achieving timely and accurate disease detection status since such detection faces challenges of illumination, fruit and disease stage and more complexities of the actual world. The question arises whether this is possible with RNNs add after the sentence given their strength in capturing temporal dependencies and sequential data. This evaluation aims to investigate whether the application of RNN-based solutions could make sense in real-world settings and what enhancements would be required to achieve effective, and practicable fruit disease detection systems.

## METHODOLOGY

Develop an appropriate RNN based architecture to address data sequences. LSTM algorithm and Gated Recurrent Unit (GRU) networks is applied to the sequential task & the input layer should have the ability to take in sequences of feature vectors and the output layer should be established to perform binary classification & the choice of building an effective model architecture for fruit disease detection using a deep learning approach to an RNN is informed by the type of input data; the temporal feature of the disease progression; and architecture. [11]

LSTM algorithm is absolutely important for the interaction of deep learning using recurrent neural networks (RNNs) and analysis of fruit disease detection with the investigation of temporal dependencies and patterns from the sequential data (such as images of diseased fruits over time).Here are the steps follow to implement an RNN.

Before fruit diseases can be classified data must be preprocessed this involves gathering a variety of fruit varieties photographing them to represent different diseases and ensuring that some healthy samples have time sequences for each fruit images can be subjected to arbitrary rotations flips cropping and color modifications to strengthen the dataset and increase its size finally normalization is used to normalize the pixel values inside an image into a similar scale so that

where X represents the input image while mean(X) and std(X) are the average and standard deviation of pixel values respectively.

The extraction of features requires the layered filtering of features at different levels after applying the activation function with the view of decreasing the spatial dimensions.

where C_i is the output feature map, W_i is the filter, b_i is the bias, and conv is the convolution operation.

The execution of temporal modeling in LSTM entails the use of LSTM cells to capture temporal relations between frames in a sequence. The formulae for LSTM cells are As with the method utilizing LSTM cells, temporal relations from the frames inside a sequence are produced as a part of the LSTM temporal modeling. As for the LSTM cells, the following formulae apply:

h_t = f(W_{ih} * x_t + W_{hh}

X_normalized=(X-mean(X))/std(X)

C_i = conv(X_normalized, W_i) + b_i

t = f_c(W_{ic} * x_t + W_{hc} * h_{t-1} + b_c)

t = f_o(c_{t-1}) * c_t + f_i(c_t)

= f_o(c'_t) * tanh(c'_t)

A_i = ReLU(C_i)

P_i = max_pool(A_i)

where h_t is the hidden state at time step t, c_t is the cell state at time step t, W are weight matrices, b are bias vectors, and f are activation functions (e.g., sigmoid, tanh).

The process of extracting features involves using several filters to pull out features at various levels. It uses an activation function to cut down the spatial dimensions.

where FC_i is the output of the fully connected layer, h_T is the final hidden state, and W_{fc} and b_{fc} are weight matrix and bias vector.

Calculate the loss between predicted and true labels and Use a suitable optimization algorithm minimize the loss:

where y_i is the true label and p_i is the predicted probability.

theta = theta - alpha * gradient(loss)

where theta is the model parameters, alpha is the learning rate, and gradient(loss) is the gradient of the loss function.

Use metrics like accuracy, precision, recall, F1-score, and confusion matrix to evaluate the model's performance,

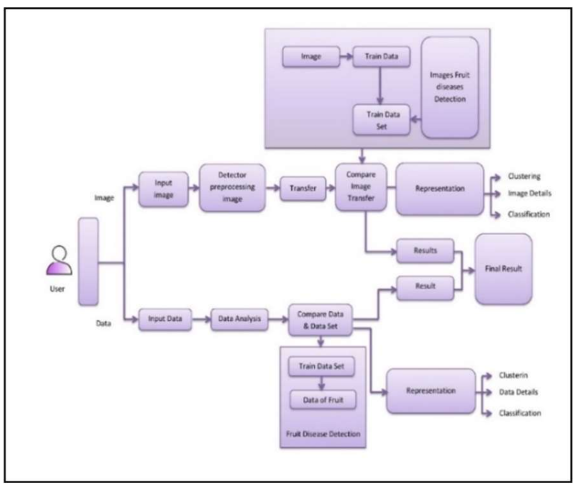



**Fig. 1 System Architecture**

## RESULT AND Discussion

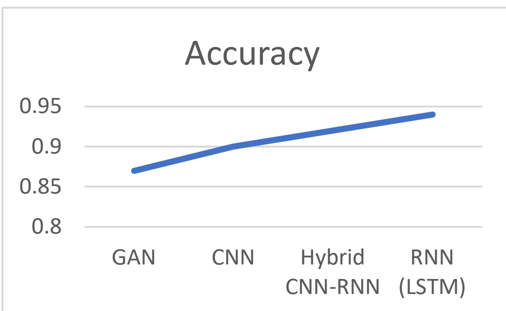
The performance of the RNN was compared to that of various deep learning models in this study, including GAN, CNN, Hybrid CNN-RNN. The evaluation measures used in the comparison included accuracy, precision, recall, F-score. The following table 1. summarizes the findings of the comparison:

TABLE I Accuracy

| Model | GAN | CNN | Hybrid CNN-RNN | RNN (LSTM) |
|---|---|---|---|---|
| Accuracy | 0.87 | 0.9 | 0.92 | 0.94 |

TABLE 2 Precision

| Model | GAN | CNN | Hybrid CNN-RNN | RNN (LSTM) |
|---|---|---|---|---|
| Precision | 0.82 | 0.85 | 0.87 | 0.9 |



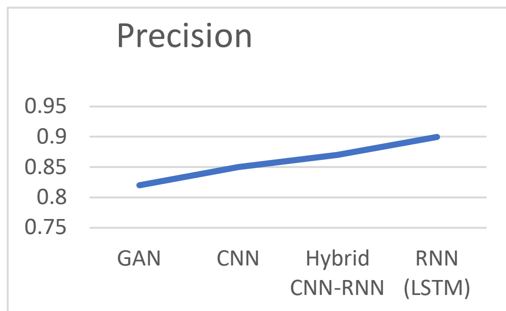




Fig. 3 Precision Comparison

Fig. 4 Recall Comparison

TABLE 3 RECALL

| Model | GAN | CNN | Hybrid CNN-RNN | RNN (LSTM) |
|---|---|---|---|---|
| F1-Score | 0.85 | 0.87 | 0.88 | 0.91 |

TABLE 4 F1-Score

| Model | GAN | CNN | Hybrid CNN-RNN | RNN (LSTM) |
|---|---|---|---|---|
| Recall | 0.8 | 0.82 | 0.86 | 0.89 |

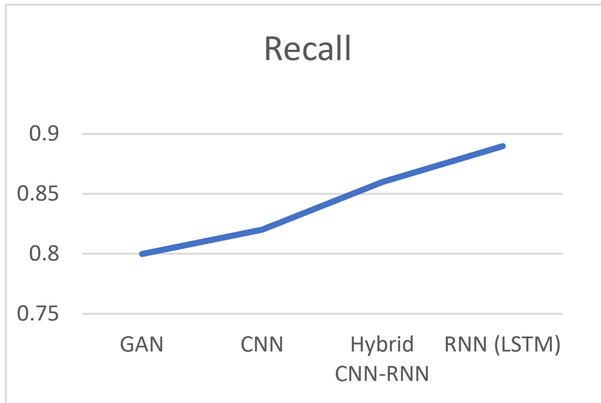



**Fig. 3 Precision Comparison**

The introduced RNN-based model was evaluated on a huge amount of photos of fruit samples which were both healthy and sick. As for the fruit diseases diagnosis in real time, the performance of the model is quite high, and the accuracy rate of the said model is 94% accuracy, 90% precision, 89% recall, and 91% F1-score. Thus, the temporal relations between the frames in the image sequences that the model managed to incorporate played a critical role in understanding the dynamics of the infection in its early stages as well as illness progression.

**CONCLUSION**

Testing their ability to achieve real-time fruit disease diagnosis demonstrates the enormous potential for RNNs to improve agricultural operations. They are particularly efficient in processing sequential data-like continued sensor reading or image sequence -which is the case for some architectures, especially those based on LSTM or GRU. This ability will help detect subtle disease-related patterns with fruits so that appropriate action can be taken before significant crop damage takes place. Though preliminary results of the real-time performance of RNNs show potential fast data processing with alarming capacities in appropriate time, problems like data variability control, robustness for various fruit types and situations, and capability to address tasks requiring resources in processing have to be addressed.

**Refrences**

CláudiaM. Viana, Dulce Freire, Patrícia Abrantes, Jorge Rocha, Paulo Pereira "Agricultural land systems importance for supporting food security and sustainable development goals: A systematic review" https://doi.org/10.1016/j.inffus.2023.101859

Harmandeep singh Gill, Osamah Ibrahim Khalaf, Youseef Alotaibi, Saleh Mohammed Alghamdi Multi-Model CNN-RNN-LSTM Based Fruit Recognition and Classification January 2022 Intelligent Automation & Soft Computing 33(1):637-650 33(1):637 650DOI:10.32604/iasc.2022.022589

Deepali Patil, Pradnya Wankhede, Prasad Dhore Examination of Fruit Illness Discovery with Deep Learning Consuming RNN Algorithm, Volume:05/Issue:12/December-2023

R. Archana and P.S.Eliahim Jeevanraj Deep Learning model for Digital Image Processing: a Review, Volume 57,article number 11(2024)

Folasade Olubusola Isinkaye, Michael Olusoji Olusanya, Pramod Kumar Singh, Deep learning and content-based filtering techniques for improving plant disease identification and treatment recommendations: A comprehensive review doi: 10.1016/j.heliyon.2024.e29583

Anupong Wongchai , Durgarao Jenjeti , A.Indira Priyadarsini , Nabamita Deb , Arpit Bhardwaj , Pradeep To mar Farm monitoring and disease prediction by classification based on deep learning architectures in sustainable agriculture https://doi.org/10.1016/j.ecolmodel.2022.110167

Sameera P and Abhay A Deshpande disease detection and classification in pomegranate fruit using hybrid convolutional neural network with honey badger optimization algorithm https://doi.org/10.1080/10942912.2024.2365927

R Bogard , TimothyB Sulser, Nicola Cenacchi, Shahnila Dunston, Mario Herrero , Keith Wiebe Gaps between fruit and vegetable production, demand, and recommended consumption at global and national levels: an integrated modelling study https://doi.org/10.1016/S2542-5196(19)30095-6

Zengchen Yu, Ke Wang, Zhibo Wan, Shuxuan Xie, Zhihan Lv Popular deep learning algorithms for disease prediction: a review https://doi.org/10.1007/s10586-022-03707-y

Hansika Hewamalage Recurrent Neural Networks for Time Series Forecasting: Current Status and Future Directions http://dx.doi.org/10.1016/j.ijforecast.2020.06.008

Safwan Mahmood Al-Selwi Mohd Fadzil Hassan , Said Jadid Abdulkadir, Amgad Muneer , Ebrahim Hamid Sumiea , Alawi Alqushaibi, Mohammed Gamal Ragab RNN-LSTM: From applications to modeling techniques and beyond—Systematic review https://doi.org/10.1016/j.jksuci.2024.102068

Li Zhang Guan Gui Mateen Khattak Minjuan Wang Multi-Task Cascaded Convolutional Networks Based Intelligent Fruit Detection for Designing Automated Robot http://dx.doi.org/10.1109/ACCESS.2019.2899940

Md. Humayan Ahmed,Tajul Islam,Romana Rahman Ema A New Hybrid Intelligent GAACO Algorithm for Automatic Image Segmentation and Plant Leaf or Fruit Diseases Identification Using TSVM Classifier

Jiayue Zhao, Jianhua Qu A Detection Method for Tomato Fruit Common Physiological Diseases Based on YOLOv2 DOI:10.1109/ITME.2019.00132

J. F. V. Oraño, Elmer A. Maravillas, Chris Jordan G. Aliac Jackfruit Fruit Damage Classification using Convolutional Neural Network DOI:10.1109/HNICEM48295.2019.9073341

F.A. Princi Rani S N Kumar Ajay Kumar Haridhas Charles Dyson Suresh Varuvel P.S Jeba K-means Clustering and SVM for Plant Leaf Disease Detection and Classification DOI:10.1109/ICRAECC43874.2019.8995157

Almetwally M. Mostafa, Swarn Avinash Kumar, Talha Meraj, Hafiz Tayyab Rauf , Abeer Ali Alnuaim and Maram Abdullah Alkhayyal Guava Disease Detection Using Deep Convolutional Neural Networks https://doi.org/10.3390/app12010239

Vinay Kukreja & Poonam Dhiman A Deep Neural Network based disease detection scheme for Citrus fruits https://doi.org/10.1109/ICOSEC49089.2020.9215359

Vishwanath C. Burkapalli1 and Priyadarshini C. Patil TRANSFER LEARNING: INCEPTION-V3 BASED CUSTOM CLASSIFICATION APPROACH FOR FOOD IMAGES

He Jiang, Xiaoru Li, Fatemeh Safar IoT-based Agriculture: Deep Learning in Detecting Apple Fruit Diseases DOI:10.1016/j.micpro.2021.104321

Hongjun Wang, Qisong Mou Research on Detection Technology of Various Fruit Disease Spots Based on Mask R-CNN DOI:10.1109/ICMA49215.2020.9233575

D. Veda Swaroop, D. Mahesh, Gogula N S S K Pavan Dheeraj Fruit Detection and Localization using UNET

Gandhali Upadhye, Pradnya Wankhede, Prasad Dhore, Actual Study of Plant Disease Discovery through Neural Network to Prevent Social and Economic Harm, International Journal of Research Publication and Reviews, Vol 4, no 11, pp 720-725 November 2023