Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, Dec 2022

DOI:10.48047/IJFANS/V11/I12/219

Paddy Crop Disease Detection Using Deep Learning

Dr. T. Kameswara Rao[1], Professor, Department of CSE,
Vasireddy Venkatadri Institute of Technology, Nambur, Guntur Dt., Andhra Pradesh
M. Nandini[2], **N. Bharadwaj**[3], **P. Susmitha**[4], **N. Mounika**[5]
[2,3,4,5] UG Students, Department of CSE,
Vasireddy Venkatadri Institute of Technology, Nambur, Guntur Dt., Andhra Pradesh
E-Mail ID: tkr.cse@vvit.net[1], nandinimedarametla911@gmail.com[2], bharadwajnaladala@gmail.com[3], popurisusmitha@gmail.com[4], nethikuntla.mounika1453@gmail.com[5]

Abstract

Agriculture plays a crucial role in human life, with approximately 60% of the population directly or indirectly involved in agricultural activities. Paddy is one of the essential food crops globally and is particularly significant in the Asian subcontinent. As a result of excessive use of chemicals and unpredictable weather patterns, there has been a significant increase in crop diseases. Sometimes an expert may be unavailable to identify the disease. Due to mistaken conclusions of experts, there is an unnecessary use of pesticides which will affect the yield badly, hence, it is essential to know which disease has affected the Paddy crop. Early detection of these diseases is essential to minimize the losses . To address this issue, Deep Learning models, including Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and ResNet101, were employed to detect three types of paddy crop diseases including Leaf Blast (LB), Brown Spot (BS), and Hispa along with the healthy category.

The dataset consisted of 6,061 images of three types of disease affected and healthy paddy crops, collected from Paddy Doctor Website and IRRI. ANN Model achieved an accuracy of 66.1%, CNN Model 94.3% and ResNet101 Model 98.2%.

Keywords: ANN, CNN, Deep Learning, Feature Extraction, Image Classification, Paddy Disease Detection, ResNet101

1. Introduction

The detection of diseases in paddy crops is essential for the proper management of crops, as it enables farmers to take timely and appropriate actions to prevent the spread of diseases and minimize crop losses. Paddy crop diseases can be caused by various factors, including pathogens such as fungi, viruses, bacteria and nematodes, as well as environmental factors such as temperature, humidity, and soil moisture. Recently, there has been a growing interest in using Machine Learning techniques, particularly Deep Learning, for automated detection of crop diseases from images. In this context, Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), and ResNet101 have emerged as popular models for image classification and recognition tasks. In the context of paddy crop disease detection, these models can be trained on a dataset of labeled images of healthy and diseased paddy crops to learn to recognize the different types of diseases that can affect the crop.

The following are diseases affected:

A. BS

Brown Spot beCharacterized in presence of brown or black spots. Brown Spot falls in a category of fungi within the taxonomic classification system yield reduction. Disease can be prevented with the appropriate nutrient content and evading water. [11].

Figure 1: Leaf affected by BS

B. LB

LB can afflict rice plants, affecting various parts of the leaves such as the blades. This disease is particularly prevalent in regions with periodic rainfall, low soil moisture, and cool temperatures. It can be identified by the appearance of spots with grey green spots with dark green borders [12].

Figure 2: Leaf affected by LB

C. Hispa

The presence of clear grub mining on the leaves is a clear indication of this disease, and severe infestation can cause the rice field to appear burnt. Hispa is most commonly observed in young plants. To manage this disease, it is crucial to avoid over-fertilizing the field [13].

Figure 3: Hispa infected leaf

2. Literature Survey

"Automated Diagnosis of Rice Diseases Using Deep Convolutional Neural Networks"(Jiang et al., 2018) [1]- It detects four common paddy diseases such as Bacterial Leaf Blight, Brown Spot, Rice Blast, and Sheath Blight. The authors achieved an accuracy of over 98% on their dataset of 3,078 images.

"Paddy Crop Disease Detection using Convolutional Neural Network" (Chen et al., 2020) [2] - Authors use a CNN to classify rice leaf images into healthy or diseased categories. The authors obtain results of 93.67% on their dataset of 1,440 images.

"Paddy Crop Disease Detection using Image Processing Techniques"[3] This paper uses image processing techniques to detect four common paddy diseases such as bacterial leaf blight, brown spot, rice blast, and sheath blight. The authors obtained results 92.1% on their dataset of 300 images.

"Rice Disease Recognition System Based on Leaf Image Analysis" (Zhang et al., 2019) [4] - In this study, the authors use a combination of color and texture features to classify rice leaf images into healthy or diseased categories. The authors achieved an results of 97.8% on their dataset of 320 images.

"Automated Detection of Paddy Crop Diseases using Machine Learning Techniques" (Sanju et al., 2021) [5] - This study explores the use of image processing for detecting three common paddy diseases such as Bacterial Leaf Blight, Brown Spot, and Rice Blast. The authors obtained results of 90% on their dataset of 900 images.

"Paddy crop disease detection using machine learning:A review" (Dhiman et al., 2021) [6] - This review paper provides an overview of various techniques including supervised, unsupervised, and deep learning methods. The authors also discuss obstacles and potential avenues for future investigation in this field.

"A comprehensive review of image processing and machine learning techniques for plant disease detection" (Singh et al., 2021) [7] - While not specific to paddy crops, this review paper provides a comprehensive overview of image processing and ML techniques that used for detection of paddy diseases. The authors discuss the advantages and limitations of different approaches and provide insights into future research directions.

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, Dec 2022

"Paddy crop disease detection using machine learning: A systematic literature review" (Jain and Sharma, 2021) [8] - This systematic literature review focuses specifically on detection of paddy diseases using ML. The authors analyze and compare various studies that have used machine learning techniques for paddy crop disease detection and provide insights into the strengths and limitations of these approaches.

"A review of computer vision and machine learning approaches for plant disease detection and monitoring" (Huang et al., 2021) [9] - This review paper provides a broad overview of computer vision and ML approaches used for detection and monitoring, including in the context of paddy crops. The authors discuss obstacles and potential avenues for future investigation in this field

"Detection of Paddy Crops Diseases and Early Diagnosis Using Faster Regional CNN"(Anandhan et al., 2021) [10] -In this study authors used Faster R-CNN, Mask R-CNN to detect diseases such as BS, Sheath Blight, Blast, Leaf Streak based on parameters as Height, Width, Depth tensors. Accuracy attained is 87,45% 85.4% on their dataset of 1500 images.

3. Problem Identification

Traditional methods for identifying leaf diseases rely on human vision. However, these methods can be costly and time-consuming as they require expert consultation. Additionally, some metrics depend on the individual's vision. Machine learning offers a promising solution for detecting and identifying various types of diseases, selecting appropriate treatment, and making informed decisions. Compared to human experts, machine learning methods perform consistently and reliably. To address the limitations of conventional methods, an ML technique was needed. There have been very limited advancements in the use of machine learning for detecting plant leaf diseases, and classification. [18-26]

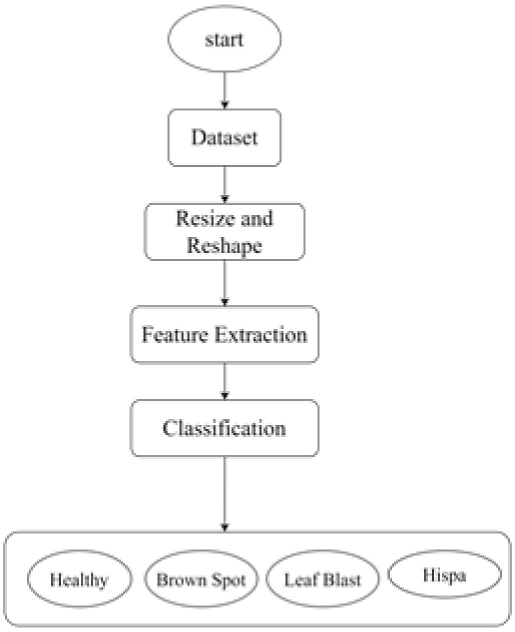
4. Proposed Methodology

Methodology consists of three steps which includes Data Collection, Model Building and Classification. The process of the proposed system is shown in Figure 4.

4.1 Data Collection

The dataset of 6061 RGB images of paddy crop is used. Leaf Blast, Brown spot and Hispa are the three classes of diseases considered for the proposed work.

The dataset is collected from the paddy doctor website and IRRI. The dataset is resized into dimension of 32*32 pixels. Here the dataset is divided in the ratio of 80% and 20%.



4.2 Feature Extraction

Shape feature extraction

One straightforward method is to determine the width and height of the image **Figure 4**: Process of Proposed System by counting the pixels that make up the object.

If shape is

- Circular or oval it might be Brown spot
- Elliptical or Spindle it might be Leaf Blast
- Square-shaped it might be Hispa

Color feature extraction

If color is

- Dark brown it might be Brown spot.
- Grey green spot with dark green border might be Leaf blast.
- white it might be Hispa.

4.3 Classification

The ResNet101 Model is used for classification of paddy crop diseases because of better performance compared to ANN, CNN. By using the ResNet101 Model it can be classified as Brown Spot, Leaf Blast, Hispa or Healthy category.

5. Implementation

A system was developed using three models such as ANN, CNN, ResNet101 Architecture.

5.1 Artificial Neural Network (ANN)

Here layers are interconnected. The subsequent deeper layers receive information from the shallower ones and eventually transmit the final output data to the output layer located at the end of the network. By processing data in parallel, an ANN can perform its tasks more

ISSN PRINT 2319 1775 Online 2320 7876

Research paper © 2012 IJFANS. All Rights Reserved, UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, Dec 2022

efficiently, resulting in faster processing times. However, when dealing with paddy leaf images that exhibit similar disease colors and shapes, the system may face difficulty in accurately classifying these diseases, even when using an artificial system.

Hence, ANN is used to determine the performance of ANN using shape and colour features. In the Project, a total of 4 hidden layers are used. This model achieved an accuracy of 66.1%. Figure 5 shows the classification of paddy diseases using ANN Architecture is shown in [14].

5.2 Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a type of neural network that can take an image as input and differentiate between different objects or features in the image. Compared to other classification methods, CNNs require less pre-processing of data. The CNN architecture consists of three types of layers: convolution layer, pooling layer, and fully connected layer.

The below Figure 6 is the Working of CNN Architecture.

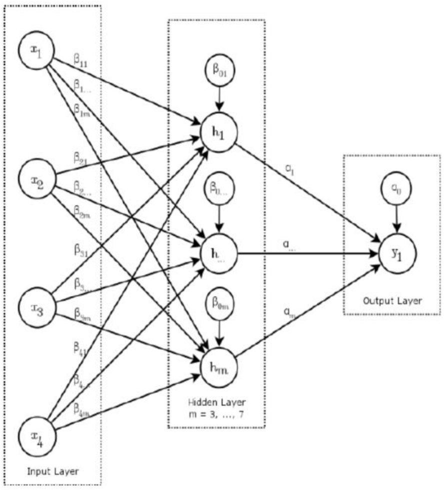


Figure 5: ANN Architecture to classify paddy crop diseases

Convolution Layer:

By applying a set of filters to the input data, this layer learns features from smaller sections of the image.

Max Pooling:

During input processing, the pixel with the highest value is chosen and passed to the output.

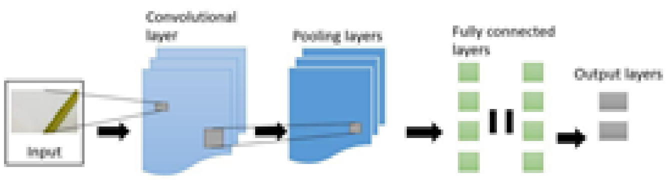


Figure 6: CNN Architecture to classify paddy crop diseases

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, Dec 2022

Fully Connected Layer (Dense):

This layer, located near the end of a Convolutional Neural Network, is capable of identifying features that are highly relevant to the output class. It produces a one-dimensional vector by flattening the results obtained from the pooling layer.

Dropout Layer:

This technique is utilized to address the issue of model overfitting by randomly eliminating a subset of neurons within a layer, which is typically linked to the fully connected layer.

SoftMax Layer:

The final layer of the network aids in categorizing individual input images from the dataset into multiple classes.

Output Layer:

The ultimate classification outcome is held by the output layer.

5.3 ResNet101

ResNet101 is an architecture consisting of 101 layers with weights. To address the issue of vanishing gradient, Residual Blocks were introduced in this architecture. Skip connections, a technique where activations of a layer are connected to subsequent layers by skipping certain layers in between, are employed to create residual blocks. ResNets are formed by stacking multiple residual blocks together. To classify the output of the images, a classification block is used. ResNet uses residual learning units to prevent the degradation of deep neural networks. This unit is beneficial as it enhances classification accuracy without increasing the model's complexity.

The RGB images of the paddy dataset are resized and reshaped before passing through the ResNet 101 model, which was pre-trained on the Imagenet dataset. The dataset is initially processed through the first Convolutional layer to extract feature maps, followed by down-sampling through the pooling layer. Subsequently, the data is passed through the remaining convolutional layers in the residual blocks for additional feature extraction. The resulting output is then provided to fully connected layers for classification, distinguishing between Brown Spot, Leaf Blast, Hispa, and Healthy categories.

6. Results & Conclusion

Several experiments were carried out by dividing the complete dataset into varying ratios of training and testing sets. The proposed RESNET model, which was the best among the three models evaluated, exhibited a classification accuracy of 98.2% for an 80%-20% training-testing split.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, Dec 2022

In comparison to the ANN and CNN models,ResNet101 demonstrated the highest accuracy following training of the three models. Consequently, it is determined that ResNet101 is a viable solution for identifying and categorizing diseases affecting paddy crops. Table 1 provides a comparative summary of experimental findings.

Model	ANN	CNN	ResNet101
Accuracy	66.1%	94.2%	98.2%
Precision	49.7%	93.8%	98.1%
Recall	59.1%	94.3%	98.3%
F1-score	53.8%	94.4%	98.2%

Table 1: Comparison of Models

Figure 7 represents the Confusion Matrix obtained for ANN.

Below Figure 8 shows Confusion Matrix of CNN and Figure 9 shows Confusion Matrix of ResNet101.

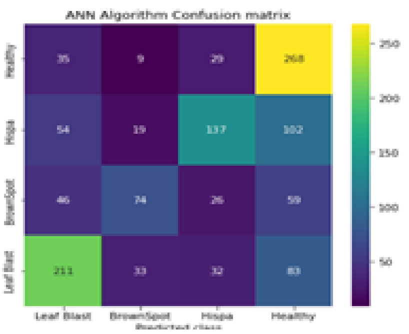


Figure 7 : Confusion Matrix of ANN

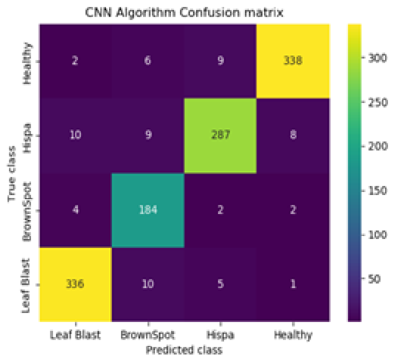


Figure 8: Confusion Matrix of CNN

Figure 9: Confusion Matrix of ResNet101

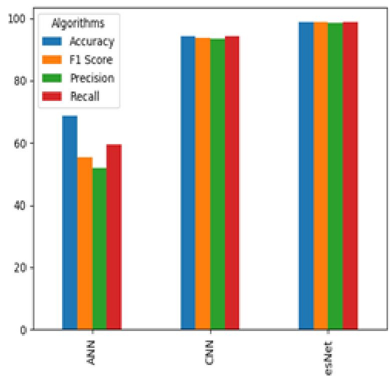


Figure 10: Comparison Graph

Testing

 UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, Dec 2022

Testingis done by using ResNet101 model because ResNet101 model achieved high accuracy compared to ANN, CNN. Therefore, the ResNet101 model proves to be effective in identifying diseases affecting paddy crops. In testing, an image is uploaded to detect whether it is healthy or it is suffering from any disease and also it givesoutput as not a paddy leaf image if other than paddy image is given.

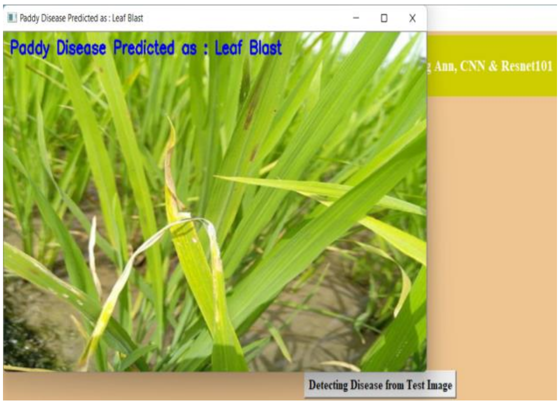


Figure 11: Detecting Leaf Blast Disease

Above Figure 11 shows detection of Leaf Blast, Figure 12 shows Healthy leaf, Figure 13 shows Detection of Brown Spot Disease and Figure 14 shows Detection of Hispa Disease.

Figure 12: Detecting Healthy leaf

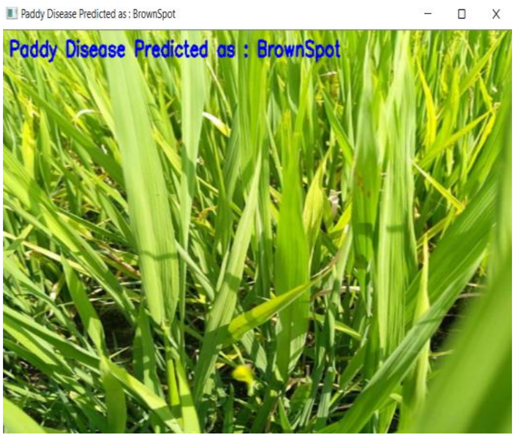


Figure 13: Detecting Brown Spot Disease

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, Dec 2022

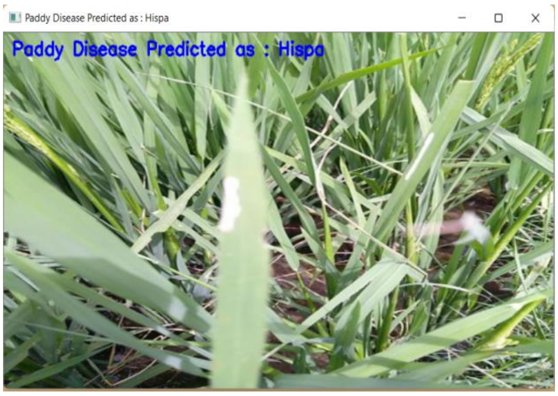


Figure 14: Detecting Hispa Disease

7. Limitations & Future Scope

Following are the limitations:

- The models are designed to detect only specific crop diseases such as Leaf Blast, Brown Spot and Hispa.
- They may be unable to recognize new or emerging diseases or detect diseases in other crops.

For further extension of the project following can be used:

The scope of the project can be expanded by incorporating additional leaf diseases that affect paddy crops, utilizing more extensive datasets, examining alternative models for faster detection and by performing Preprocessing Techniques.

References

[1] Lu, Y., Yi, S., Zeng, N., Liu, Y., & Zhang, Y. (2017). Identification of rice diseases using deep convolutional neural networks. Neurocomputing, 267, 378-384.

[2] Zhang, J., Yang, Y., Feng, X., Xu, H., Chen, J., & He, Y. (2020). Identification of bacterial blight resistant rice seeds using terahertz imaging and hyperspectral imaging combined with convolutional neural networks. Frontiers in Plant Science, 11, 821.

[3] Li, Y., Nie, J., & Chao, X. (2020). Do we really need deep CNN for plant diseases identification? Computers and Electronics in Agriculture, 178, 105803.

[4] Liang, W. J., Zhang, H., Zhang, G. F., & Cao, H. X. (2019). Rice blast disease recognition using a deep convolutional neural network. Scientific reports, 9(1), 2869.

[5] SANJU, S. K., & VELAMMAL, D. B. (2021). An automated detection and classification of plant diseases from the leaves using image processing and machine learning techniques: A state-of-the-art review. Annals of the Romanian Society for Cell Biology, 15933-15950.

[6] Wynants, L., Van Calster, B., Collins, G. S., Riley, R. D., Heinze, G., Schuit, E., ... & van Smeden, M. (2020). Prediction models for diagnosis and prognosis of covid-19: systematic review and critical appraisal. bmj, 369.

[7] Varshney, D., Babukhanwala, B., Khan, J., Saxena, D., & Kumar Singh, A. (2021, June). Machine learning techniques for plant disease detection. In 2021 5th International Conference on Trends in Electronics and Informatics (ICOEI) (pp. 1574-1581). IEEE.

[8] Sharma, P., Sogani, A., & Sharma, A. (2021). A Review of Crop Diseases Identification Using Convolutional Neural Networks. Information Management and Machine Intelligence: Proceedings of ICIMMI 2019, 163-168.

[9] Huang, M. Q., Ninić, J., & Zhang, Q. B. (2021). BIM, machine learning and computer vision techniques in underground construction: Current status and future perspectives. Tunnelling and Underground Space Technology, 108, 103677.

[10] Anandhan, K., & Singh, A. S. (2021, March). Detection of paddy crops diseases and early diagnosis using faster regional convolutional neural networks. In 2021 international conference on advanced computing and innovative technologies in engineering (ICACITE) (pp. 898-902). IEEE.

[11] http://www.knowledgebank.irri.org/training/fact-sheets/pest-management/diseases/item/brown-spot

[12] http://www.knowledgebank.irri.org/training/fact-sheets/pest-management/diseases/item/blast-leaf-collar

[13] http://www.knowledgebank.irri.org/training/fact-sheets/pest-management/insects/item/rice-hispa

[14] https://www.researchgate.net/publication/348343662_Classification_of_rice_leaf_diseases_using_artificial_neural_network

[15] https://paddydoc.github.io/dataset

[16] Narmadha, R. P., &Arulvadivu, G. (2017, January). Detection and measurement of paddy leaf disease symptoms using image processing. In 2017 International Conference on Computer Communication and Informatics (ICCCI) (pp. 1-4). IEEE.

[17] Rautaray, S. S., Pandey, M., Gourisaria, M. K., Sharma, R., & Das, S. (2020). Paddy crop disease prediction—a transfer learning technique. International Journal of Recent Technology and Engineering, 8(6), 1490-1495.

[18] Sri Hari Nallamala, et al., “A Literature Survey on Data Mining Approach to Effectively Handle Cancer Treatment”, (IJET) (UAE), ISSN: 2227 – 524X, Vol. 7, No 2.7, SI 7, Page No: 729 – 732, March 2018.

[19] Sri Hari Nallamala, et.al., “An Appraisal on Recurrent Pattern Analysis Algorithm from the Net Monitor Records”, (IJET) (UAE), ISSN: 2227 – 524X, Vol. 7, No 2.7, SI 7, Page No: 542 – 545, March 2018.

[20] Sri Hari Nallamala, et.al, “Qualitative Metrics on Breast Cancer Diagnosis with Neuro Fuzzy Inference Systems”, International Journal of Advanced Trends in Computer

ISSN PRINT 2319 1775 Online 2320 7876

 UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, Dec 2022

Science and Engineering, (IJATCSE), ISSN (ONLINE): 2278 – 3091, Vol. 8 No. 2, Page No: 259 – 264, March / April 2019.

[21] Sri Hari Nallamala, et.al, "Breast Cancer Detection using Machine Learning Way", International Journal of Recent Technology and Engineering (IJRTE), ISSN: 2277-3878, Volume-8, Issue-2S3, Page No: 1402 – 1405, July 2019.

[22] Sri Hari Nallamala, et.al, "Pedagogy and Reduction of K-nn Algorithm for Filtering Samples in the Breast Cancer Treatment", International Journal of Scientific and Technology Research, (IJSTR), ISSN: 2277-8616, Vol. 8, Issue 11, Page No: 2168 – 2173, November 2019.

[23] Kolla Bhanu Prakash, Sri Hari Nallamala, et al., "Accurate Hand Gesture Recognition using CNN and RNN Approaches" International Journal of Advanced Trends in Computer Science and Engineering, 9(3), May – June 2020, 3216 – 3222.

[24] Sri Hari Nallamala, et al., "A Review on 'Applications, Early Successes & Challenges of Big Data in Modern Healthcare Management'", Vol.83, May - June 2020 ISSN: 0193-4120 Page No. 11117 – 11121.

[25] Nallamala, S.H., et al., "A Brief Analysis of Collaborative and Content Based Filtering Algorithms used in Recommender Systems", IOP Conference Series: Materials Science and Engineering, 2020, 981(2), 022008.

[26] Nallamala, S.H., Mishra, P., Koneru, S.V., "Breast cancer detection using machine learning approaches", International Journal of Recent Technology and Engineering, 2019, 7(5), pp. 478–481.