IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

PADDY LEAVE DISEASE CLASSIFICATION USING ARTIFICAL INTELLIGENCE

Ramapriya S [1] ,Priyadharshini N [2] ,Durga P[3], Prabdevi E [4], Janani P[5] ,Maheswhari K[6]

Assistant Professor[1], UG Students[2,3,4,5,6], Department of Electronics and Communication Engineering,
Adhi college of engineering And Technology, Kanchipuram-631 605.

***Abstract*-**Smart farming system using necessary infrastructure is an innovative technology which helps in improving the quality and quantity of agricultural production in the country. Rice leaf disease has long been one of the major threats to field security as it dramatically reduces crop yield and compromises its quality. Accurate and precise diagnosis of diseases has been a significant challenge and recent advances in computer vision by deep learning have led the way for camera-assisted disease diagnosis for rice leaves. It described the innovative solution that provides efficient disease detection and deep learning with Convolutional Neural Networks (CNN) which has achieved great success in classification of various rice foliar diseases. A variety of neuron-wise and layer-wise visualization methods were applied using a CNN, trained with a publicly available paddy leaf disease given image dataset. So, it was observed that neural networks can capture the colors and textures of lesions specific to respective diseases upon diagnosis, which resembles human decision-making.

***Index Terms* -**Deep Learning, TensorFlow, Keras, CNN

I.INTRODUCTION:

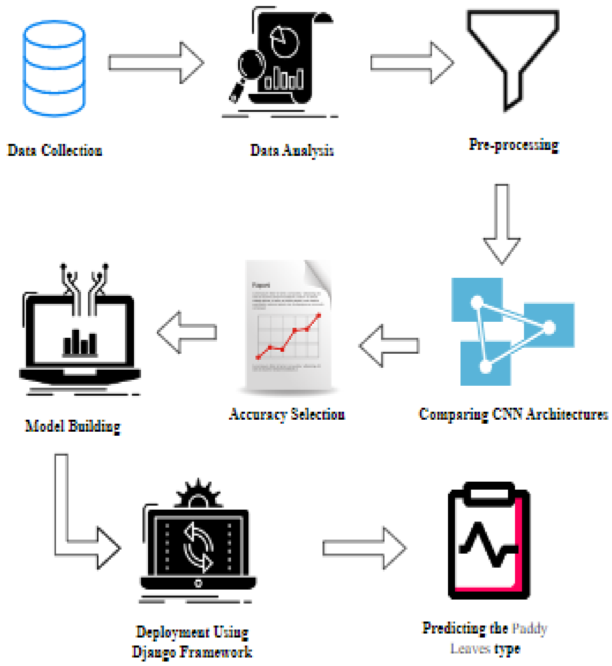
Rice blast is a fungal disease caused by Pyriculia oryzae. The disease can infect all growth stages of rice and all aerial parts of the plant (leaf, neck and node). Symptoms: The disease infects all parts of the plant except the roots but is more severe on leaves, nodes and panicles. This paper proposes a deep learning-based model that is trained using a public dataset containing images of healthy and diseased crop leaves. The model serves its purpose by classifying images of leaves into diseased categories based on patterns of damage. The four most important strategies for rice disease management are crop rotation, planting resistant varieties, planting in warm soils, and using fungicides when necessary. An integrated approach using all these methods is most effective and profitable.

II.RELATED WORK:

Synthetic aperture radar (SAR) can be used to obtain remote sensing images of different growth stages of crops under all weather conditions. Such time-series SAR images can provide an abundance of temporal and spatial features for use in large-scale crop mapping and analysis. In this study, we propose a temporal feature-based segmentation (TFBS) model for accurate crop mapping using time-series SAR images. The results show that the TFBS model outperforms LSTM, UNET, and Conv LSTM models in the study area. The kappa, F-score, precision, and recall scores of the TFBS model are significantly higher than those of the other models. The abundant temporal features mined from raw time-series SAR images by the LSTM module of TFBS achieve higher J–M and TD values than raw images, which makes TFBS more suitable for time-series image segmentation than UNET. TFBS also shows the best spatial and temporal generalizability when the trained models are applied to a different year or place. This study also evaluates the effect of data augmentation on the accuracy of the TFBS model, revealing that the generalizability of the TFBS model demonstrates substantial improvement after data augmentation, showing higher accuracies than the TFBS model without data augmentation.To classify the paddy leaf diseases. We planned to design a deep learning technique, so that a person with lesser expertise in software should also be able to use it easily. It proposed system for predicting paddy leaf diseases. It explains the experimental analysis of our methodology. A Different number of images is collected for each disease that was classified into training images and testing images. The primary attributes of the image have relied upon the shape and texture-oriented features. Using CNN Algorithm for getting more accuracy and proper output. We are implementing more than two architectures and getting the accuracy of all the architectures and comparing. After saving the model and deployed in the Django framework.

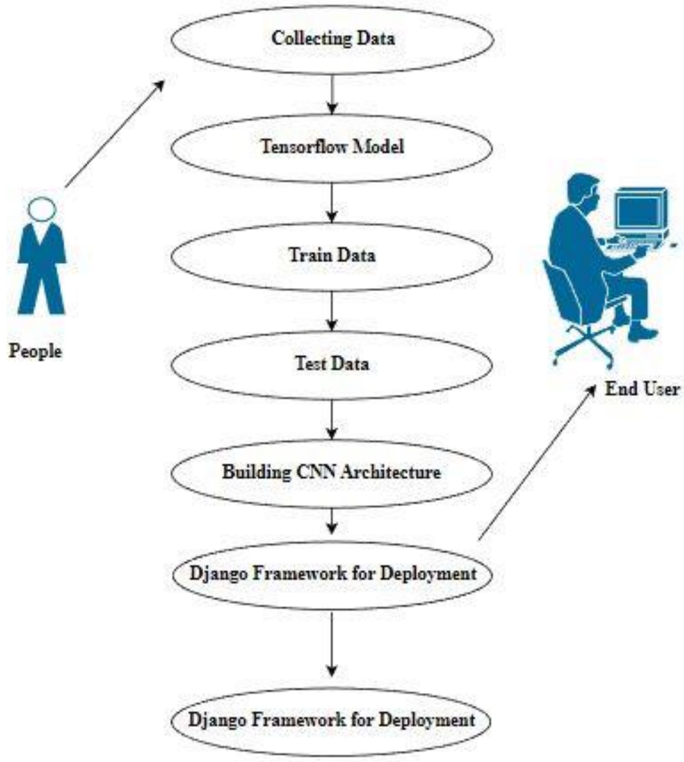
III.SYSTEM ARCHITECTURE:

Design is a meaningful engineering representation of something that is to be built. Software design is a process design which is the right way to accurately translate requirements into a finished software product. Design creates a representation, or model, providing details about the software data structure, architecture, interfaces, and components that are needed to implement the system.



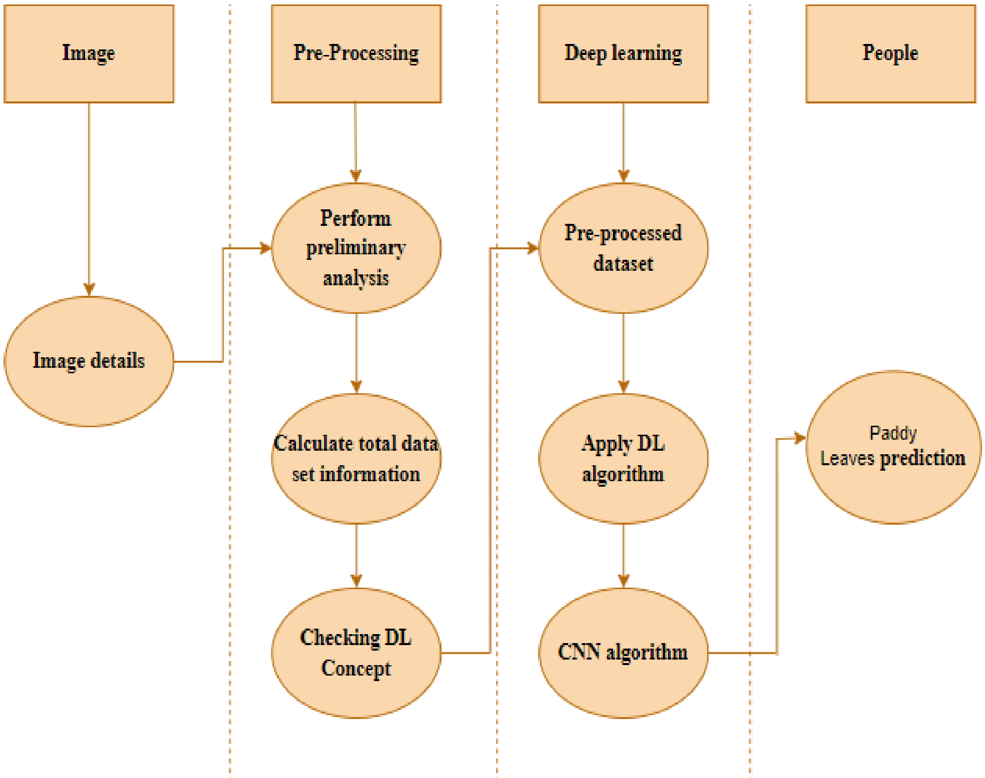
IV.METHODOLOGY:

Preprocessing and Training the model (CNN): The dataset is preprocessed such as Image reshaping, resizing and conversion to an array form. Similar processing is also done on the test image. A dataset consisting of about 4 different Paddy Leaves is obtained, out of which any image can be used as a test image for the software. The train dataset is used to train the model (CNN) so that it can identify the test image and the disease it has CNN has different layers that are Dense, Dropout, Activation, Flatten, Convolution2D, and MaxPooling2D. After the model is trained successfully, the software can identify the Paddy Leaves Classification image contained in the dataset. After successful training and preprocessing, comparison of the test image and trained model takes place to predict the Paddy Leaves.Train dataset is used to train the model (CNN) so that it can identify the test image and it has different convolution layers of CNN which are Dense, Dropout, Activation, Flatten, Convolution2D, and MaxPooling2D.After the model is successfully trained, the software can identify the classification image of paddy leaves contained in the dataset. After successful training and preprocessing, the test image and the trained model are compared to predict rice leaves.2D convolution is a fairly simple operation at heart: you start with a kernel, which is a small matrix of weights. This kernel "slides" over the 2D input data, performs an element-wise multiplication with the portion of the input currently on, and then combines the result into a single output pixel.
The kernel repeats this process for each location it slides over, transforming the 2D matrix of features into another 2D matrix of features. The output features are essentially the weighted sum (with the weights being the values of the kernel) of the input features located at the same location as the output pixel on the input layer. This is the opposite of a fully connected layer. In the above example, we have $5\times5=25$ input features, and $3\times3=9$ output features. If this were a standard fully connected layer, you would have a weighting matrix of $25 \times 9 = 225$ parameters, with each output feature being the weighted sum of each single input feature.



V.RESULTS AND CONCLUSION:

In this project, a research was developed to classify paddy leaves on static face images using deep learning techniques. This is a complex problem that has already been approached many times with different techniques. While good results have been achieved using feature engineering, this project focuses on feature learning, which is one of the promises of DL. While feature engineering is not necessary, image pre-processing boost .



Hence, it reduces noise on the input data. Nowadays, Paddy Leaves detection software includes the use of feature engineering. A solution totally based on feature learning does not seem close yet because of a major limitation. Thus, Paddy Leaves classification could be achieved by means of deep learning techniques.

VII.FUTURE ENHANCEMENT:

Further improvement on the network's accuracy and generalization can be achieved through the following practices. The first one is to use the whole dataset during the optimization. Using batch optimization is more suitable for larger datasets. Another technique is to evaluate Paddy Leaves one by one. This can lead to detect which Paddy Leaves are more difficult to classify. Finally, using a larger dataset for training seems beneficial. However, such a dataset might not exist nowadays. Using several datasets might be a solution, but a careful procedure to normalize them is required. Finally, using full dataset for training, pre-training on each Paddy Leaves and using a larger dataset seem to have the possibility to improve the network's performance. Thus, they should be addressed in future research on this topic.

VIII.REFERNCES:

[1] H. C. J. Godfray et al., "Food security: The challenge of feeding 9 billionpeople," Science, vol. 327,no.5967,pp. 812–818, Feb. 2010.
[2] D. Boddiger, "Boosting biofuel crops could threaten food security,Lancet, vol. 370, no. 9591, 9924,Sep. 2007.
[3] C. C. Funk and M. E. Brown, "Declining global per capita agricultural production and warming oceans threaten food security," Food Secur., vol. 1, no. 3, pp. 271–289, Sep. 2009.
[4] The State of Food Security and Nutrition in the World 2020. Transform-ing Food Systems for Affordable Healthy Diets, FAO, IFAD, UNICEF, WFP, and WHO, Rome, Italy, 2020.
[5] P. Thenkabail, M. Hanjra, V. Dheeravath, and M. Gumma, "A holistic view of global croplands and their water use for ensuring global food security in the 21st century through advanced remote sensing and non- remote sensing approaches," Remote Sens., vol. 2, no. 1, pp. 211–261, Jan. 2010.
[6] M. E. Brown, "Remote sensing technology and land use analysis in food security assessment," J. Land Use Sci., vol. 11, no. 6, pp. 623–641,Nov. 2016.
[7] Y. Xu et al., "Tracking annual cropland changes from 1984 to 2016 using time-series Landsat images with a change-detection and post- classification approach: Experiments from three sites in Africa," Remote Sens. Environ., vol. 218, pp. 13–31, Dec. 2018.
[8] D. B. Lobell, D. Thau, C. Seifert, E. Engle, and B. Little, "A scalable satellite-based crop yield mapper," Remote Sens. Environ.,

vol. 164, pp. 324–333, Jul. 2015.

[9] L. Yang, L. Wang, J. Huang, L. R. Mansaray, and R. Mijiti, "Monitoring policy-driven crop area adjustments in northeast China using Landsat-8 imagery," Int. J. Appl. Earth Observ. Geoinf., vol. 82, Oct. 2019, Art. no. 101892.

[10] Q. Yuan et al., "Deep learning in environmental remote sensing: Achievements and challenges," Remote Sens. Environ., vol. 241, May 2020, Art. no. 111716.

[11] X. X. Zhu et al., "Deep learning in remote sensing: A comprehensive review and list of resources," IEEE Geosci. Remote Sens. Mag., vol. 5, no. 4, pp. 8–36, Dec. 2017.

[12] M. Boschetti et al., "PhenoRice: A method for automatic extraction of spatio-temporal information on rice crops using satellite data time series," Remote Sens. Environ., vol. 194, pp. 347–365, Jun. 2017.

[13] G. Azzari and D. B. Lobell, "Landsat-based classification in the cloud: An opportunity for a paradigm shift in land cover monitoring," Remote Sens. Environ., vol. 202, pp. 64–74, Dec. 2017.

[14] X. Xiao et al., "Mapping paddy rice agriculture in southern China using multi-temporal MODIS images," Remote Sens. Environ., vol. 95, no. 4, pp. 480–492, 2005.

[15] J. Dong et al., "Mapping paddy rice planting area in northeastern Asia with Landsat 8 images, phenology-based algorithm and Google Earth Engine," Remote Sens. Environ., vol. 185, pp. 142–154, Nov. 2016.

[16] L. Yang, L. Mansaray, J. Huang, and L. Wang, "Optimal segmenta- tion scale parameter, feature subset and classification algorithm for geographic object-based crop recognition using multisource satellite imagery," Remote Sens., vol. 11, no. 5, p. 514, Mar. 2019.

[17] J. E. Ball, D. T. Anderson, and C. S. Chan, "Comprehensive survey of deep learning in remote sensing: Theories, tools, and challenges for the community," J. Appl. Remote Sens., vol. 11, no. 4, Sep. 2017, Art. W. Li, Z. Niu, R. Shang, Y. Qin, L. Wang, and H. Chen, "High-resolution mapping of forest canopy height using machine learning by coupling ICESat-2 LiDAR with Sentinel-1, Sentinel-2 and Landsat-8 data," Int.J.Appl.Earth Observ. Geoinf., vol. 92, Oct. 2020, Art. no. 102163.