EAI Endorsed Transactions
on Internet of Things

Research Article EAI.EU

Identification and Categorization of Yellow Rust Infection in Wheat through Deep Learning Techniques

Mamatha Mandava[1], Surendra Reddy Vinta[2, *], Hritwik Ghosh[3], Irfan Sadiq Rahat[4]

[1,2,3,4] School of Computer Science and Engineering (SCOPE), VIT-AP University, Amaravati, Andhra Pradesh, India

Abstract

The global wheat industry faces significant challenges due to yellow rust disease, This is induced by fungus Puccinia striiformis, as it leads to substantial crop losses and economic impacts. Timely detection and classification of the disease are essential for its effective management and control. In this study, we investigate the potential of DL and ML techniques for detecting and classifying yellow rust disease in wheat. We utilize three state-of-the-art CNN models, namely ResNet50, DenseNet121, and VGG19, to analyze wheat leaf images and extract relevant features. These models were developed and refined using a large dataset of annotated wheat photos. Encompassing both healthy plants and those affected by yellow rust disease. Furthermore, we examine the effectiveness of data augmentation and transfer learning in enhancing classification performance. Our findings reveal that the DL-based CNN models surpass traditional machine learning techniques in detecting and classifying yellow rust disease in wheat. Among the tested CNN models, EfficientNetB3 demonstrates the best performance, emphasizing its suitability for large-scale and real-time monitoring of wheat crops. This research contributes to the development of precision agriculture tools, laying the groundwork for prompt intervention and management of yellow rust disease, ultimately minimizing yield loss and economic impact on wheat production.

Keywords: Puccinna striiformis, wheat production, yield loss, detection, classification, deep learning, ML, Convolutional neural networks (CNN), ResNet50, DenseNet121, VGG19, wheat leaf images, data augmentation, transfer learning, performance, precision agriculture, disease management

Received on 05 October 2023, accepted on 07 December 2023, published on 14 December 2023

doi: 10.4108/eetiot.4603

*Corresponding author. Email: vsurendra.cseryan@gmail.com

1. Introduction

The Yellow rust disease, triggered by the pathogen Puccinia striiformis, presents a substantial obstacle to global wheat production, resulting in considerable yield losses and economic repercussions **[1]**. The highly destructive nature of the disease warrants early detection and classification to facilitate effective management and control strategies **[2].** Yellow rust disease has been recorded in over 60 different countries, resulting in significant losses in wheat yields, sometimes up to 80% **[3].** Notable epidemics have occurred in countries such as Australia, South Asia, India, Pakistan, China, New Zealand, Iran, and the United States, with considerable economic impacts **[4,5].** In addition to yield loss, the disease also negatively impacts wheat quality **[6].** The ability to monitor and control yellow rust disease is critical for minimizing economic losses. Traditionally, rust severity levels are determined visually by experts in field conditions, taking into account factors for example wheat variety, weather and climate factors and chemicals applied to protect the plants **[7].** However, this process is subject to human error and may not yield accurate results. Recent breakthroughs in information technology allow for the development of computerized algorithms for detecting structural defects in objects using just the pixel values of object photographs **[8].**

Convolutional neural networks (ConvNets) have emerged as a state-of-the-art method for automatic feature extraction and object recognition in various fields, including medicine and agriculture **[9,10].** ConvNets are particularly useful for video, image, written content, or audio classification tasks, and have been used to solve difficulties such as recognizing hand rheumatoid arthritis, diagnosing breast cancer, and identifying plant illnesses. **[11,12,13]**. Success in ConvNet-based models relies on the availability of high-quality images and appropriate network architecture **[14].** The objective of this study is to develop a ConvNet-based model that can categories wheat yellow rust infections as resistant (R), moderately resistant (MR), moderately susceptible (MS), or susceptible (S) infections.

This research is driven by the hypothesis that experts visually analyze structural changes in wheat leaves to the existence and level of yellow rust disease, and ConvNets can effectively classify these structural changes in images, allowing for accurate determination of yellow rust severity levels in wheat. To achieve this goal, we employ three state-of- the-art ConvNet models, EfficientNetB3, DenseNet121, and VGG19, which have demonstrated success in various object recognition tasks. Additionally, to increase model performance, we investigate the possibility of data augmentation and transfer learning strategies. By leveraging these advanced DL and ML methods, we aim to provide a valuable tool for researchers and producers to take timely and effective action against the disease, ultimately minimizing yield loss and economic impact on wheat production.

The structure of this essay is as follows: In Section 2, the research techniques used to select the primary studies are covered. Section 3 addresses the proposed methodology. Section 4 looks at Experimental analysis. In Section 5&6, the results and conclusions.

2. Literature Review

In the last decade, a variety of DL algorithms for the identification and classification of wheat illnesses have been introduced, including yellow rust. One such example is the work of Hussain et al. (2018) **[15],** who developed an Alex Net-based system for categorizing wheat into four groups: stem rust, yellow rust, powdery mildew, and healthy. This approach demonstrated promising results, achieving an accuracy of 84.54% in identifying the presence of yellow rust among other diseases.

Hayit et al. (2021) **[16]** developed a dataset containing images of wheat leaves infected with yellow rust, which was utilized to train, validate, and test a Yellow-Rust-Xception is the name given to a DL model. This model achieved a test accuracy of 91%, indicating its ability to predict the possibility of yellow rust in wheat as well as the extent of the infection. In addition to the Yellow-Rust-Xception model, other well-known deep learning architectures, Base models like MobileNet and ResNet were also explored, demonstrating the applicability of multiple deep learning approaches for agricultural applications.

As artificial intelligence progresses, conventional ML approaches are gradually being replaced by more advanced techniques, such as convolutional neural networks (CNNs) **[17,18,19].** CNNs have shown substantial benefits in image recognition tasks mostly because of their ability to extract deep information from raw photos automatically. Several research has used CNNs to detect illnesses in agricultural products. **[20,21,22].**

A computerized ConvNet model was then shown Koc et al. (2019) **[23]** to distinguish between normal, technically damaged, or both wheat leaves, powdery mildew, Cochliobolus heterotrophs, bacterial leaf streak, bacterial leaf blight, leaf rust, and stripe rust. They created the matrix-based CNN known as M-CNN, which had a testing accuracy of 90.1% and an average validation accuracy of 96.5%.

CNNs have also been extensively applied in the detection of defects in agricultural products**.** For instance, Zhao et al**. [24]** built a CNN-based model for identifying tomato powdery mildew, leaf mould, and cucumber downy mildew, with a 97.24% recognition accuracy. CNNs have been utilized for assessing the maturity and grading of agricultural products. Long Jiehua et al**. [25]** developed an enhanced Mask R-CNN approach for segmenting tomatoes at different stages of ripeness, achieving a mean average precision of 95.45%. This demonstrates the growing importance of CNNs in addressing diverse agricultural challenges.

Additionally, Mosisa (2019) **[29]** introduced a MosNet, created from the ground up to detect wheat rust illnesses utilizing wheat photos, including yellow rust, stem rust, and leaf rust. MOs Net achieved an accuracy of 86.62%. These studies demonstrate the potential of DL techniques ineffectively detecting and classifying yellow rust disease in wheat.

Recent advances in computer science and also in hardware technology have enhanced the acquisition, storage, and processing of excellent quality photographs dramatically. At the same time, expert-level performance has been achieved through the creation of DL algorithms inspired by the human brain. These developments have transformed AI in imaging, resulting in multiple successful research in domains as diverse as breast cancer diagnosis.

3. Description of Dataset

The dataset used in this research is composed of wheat leaf images that showcase various severity levels of yellow rust disease. The severity levels of the disease are divided into six distinct categories: Absent (0) with no observable symptoms; Resistant (R) exhibiting minimal infection evidence; Partially Resistant (PR) displaying minor to moderate infection signs; Intermediate Resistance-Susceptibility (IRS); Partially Susceptible (PS) characterized by moderate infection symptoms; and Susceptible (S) with considerable signs of infection. The dataset is divided into two distinct subsets: YELLOW-RUST-19 and RAW images. The YELLOW-RUST-19 data subset contains a total of 15,000 wheat leaf images, with an even distribution across the severity levels. Each category has 2,500 images, providing a balanced representation of the different infection levels. On the other hand, the RAW images subset consists of 5,421 wheat leaf images, with varying quantities of images per severity level: 205 for No disease, 361 for Resistant, 564 for Moderately Resistant, 1,135 for MRMS, 1,795 for Moderately Susceptible, and 1,361 for Susceptible. This comprehensive dataset will be instrumental in training and evaluating the performance of DL and ML for identification and categorization of yellow rust disease in wheat.

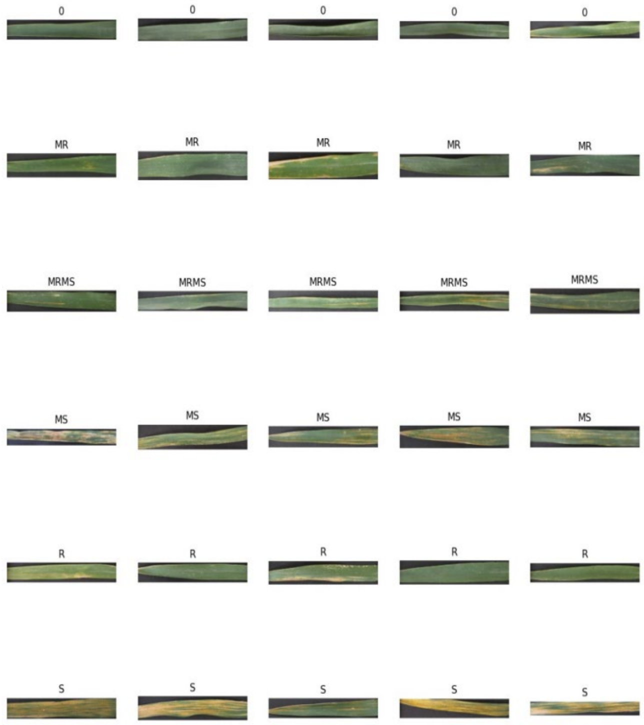


Fig.1 Severity level Images from the Data set

3.1. Preprocessing of the Dataset

For the effective detection and classification of yellow rust disease in wheat using our dataset, it is essential to preprocess the images in a manner that enhances the model's performance. Every single raw picture in the data collection undergoes a series of image preprocessing operations to create a refined and focused representation of the wheat leaves. The following steps are executed in the order mentioned:

3.2. Image Preprocessing

To create a robust deep learning model for our dataset, each raw image undergoes a series of image preprocessing steps. These operations are essential for enhancing the model's ability to accurately detect and classify yellow rust disease in wheat. The sequence of preprocessing operations includes Utilizing thresholding and morphological alterations, the RGB image's foreground is separated. Subsequently, an image of the leaf is produced by incorporating an alpha channel while preserving the RGB image. Morphological Transformations, Threshold Masking the foreground in the RGB image and creating the final leaf image by storing the RGB image with an alpha channel. Pixels with intensities above the threshold are considered part of the leaf, while those below the threshold are considered background. Morphological Transformations, such as dilation and erosion, are applied to refine the leaf's edges and eliminate any unwanted artifacts or noise. Next, Masking the foreground isolates the leaf area from the RGB image, focusing the model's attention on the region of interest. Finally, the preprocessed leaf image is saved with an alpha channel, preserving the transparency of the background and ensuring a clean, noise-free representation of the wheat leaf for further analysis by the DL model.

Thresholding

In the preprocessing phase for our data set, the Threshold operation plays a vital role in distinguishing the wheat leaf from its background. This technique entails selecting a particular pixel intensity value as the threshold. Pixels exhibiting intensities greater than this value are identified as part of the leaf, while those with lower intensities are regarded as background elements. By applying Threshold, the wheat leaf area is effectively isolated, ensuring a clear and well-defined representation for subsequent analysis by the DL and ML models.

Morphological

As part of the preprocessing process for our dataset, Morphological Transformations are employed to improve the quality of the wheat leaf images. These transformations focus on refining the leaf edges and eliminating any undesired artifacts or noise present in the images. Key techniques involved in this process include erosion and dilation, which work together to smooth out the leaf boundaries and create a more accurate representation. By implementing Morphological Transformations, we enhance the overall image quality, allowing the DL and ML models to better analyze and classify yellow rust disease in wheat.

Masking Foreground

In the preprocessing pipeline for our dataset, Masking Foreground plays an important role in concentrating the attention of the DL and ML models on the area of interest. In this step, the wheat leaf area is separated from the RGB image, effectively isolating it from any surrounding background elements. By applying Masking Foreground, we ensure that the models remain focused on the relevant leaf regions during their analysis, avoiding any distractions from unrelated background components. This technique contributes to the accuracy and efficiency of the models in detecting and classifying yellow rust disease in wheat.

Final Leaf Image Generation

The last step in the preprocessing process for our data set involves generating the final leaf image. After applying the earlier stages, including refined edges and foreground isolation, the preprocessed wheat leaf image is saved with an alpha channel. The alpha channel serves to maintain the transparency of the background, yielding a clean and noise-free depiction of the wheat leaf. This high-quality representation is then primed for subsequent analysis by the DL and ML models, ensuring precise detection and classification of yellow rust disease in wheat.

4. Experimental Analysis

Multiple DL models were employed to detect and classify yellow rust disease in wheat. These models were trained, validated, and tested using a comprehensive dataset of wheat leaf images that exhibited varying degrees of yellow rust infection. By conducting a thorough evaluation of each model's performance in terms of accuracy, loss, and validation metrics, valuable insights were gained into their effectiveness and potential for real-world applications. The process involved splitting the dataset into training, validation, and testing sets, ensuring a balanced representation of different infection levels. The deep learning models, including DenseNet121, ResNet50, and VGG19, were then trained and fine-tuned to optimize their performance in detecting and classifying yellow rust disease. Throughout the experimental analysis, the performance of each model was carefully monitored and compared, with particular attention paid to metrics such as loss, validation loss, accuracy, and validation accuracy over the course of multiple epochs. Graphical representations of these metrics provided visual insights into the models' learning progress and their ability to generalize to unseen data. The results of the experimental analysis demonstrated the potential of DL techniques in accurately detecting and classifying yellow rust disease in wheat. Each model exhibited distinct strengths and weaknesses, and their overall performance varied depending on the specific architecture and training parameters employed. By comparing and analyzing the performance of these models, researchers can gain a deeper understanding of their capabilities and make informed decisions about the most suitable models for further development and deployment in real-world agricultural settings.

4.1. Confusion Matrix

A confusion matrix is a vital evaluation tool in the field of ML and DL, providing a clear representation of a model's efficacy as a function of its ability to correctly classify data points across various categories. By presenting the results in a tabular format, the confusion matrix allows researchers to easily identify patterns and trends in the model's predictions, as well as assess its strengths and weaknesses in classifying different categories. In the context of detecting and classifying yellow rust disease in wheat, a confusion matrix would consist of rows and columns representing the true and predicted classes, respectively. Each cell in the matrix represents the number of instances where the model predicted a particular class (column) for samples that belong to a specific true class (row). The number of correct guesses is indicated by the matrix main diagonal, while the off diagonal The elements represent a total of incorrect classifications. By analyzing the confusion matrix, researchers can gain insights into the model's overall accuracy for each class. This information is essential for understanding the model's performance and identifying areas that may require further improvement or fine-tuning. For instance, a high number of false positives for a specific class might suggest that the model is overly sensitive to certain features and prone to making incorrect predictions. Conversely, a high number of false negatives might indicate that the model is failing to recognize key features that are necessary for accurate classification.

4.2. Performance of the Three Model

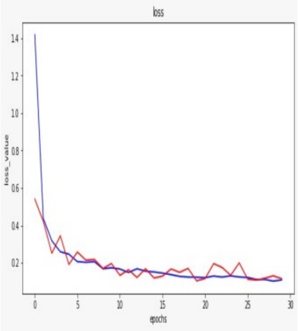
The efficacy of three cutting-edge deep learning architectures, DenseNet121, ResNet50, and VGG-19, was assessed in the context of wheat disease identification and categorization. The models were compared founded on key metrics such as loss, accuracy, and AUC. Further analysis of loss versus validation loss and accuracy versus validation accuracy per epoch provided valuable insights into each model's learning process and performance trends.

DenseNet121 delivered a notable performance, achieving a loss of 1.0320 and an AUC of 0. 8870.The model's validation loss and AUC stood at 1.1158 and 0.8787, respectively. These results demonstrate that DenseNet121 is capable of effectively detecting and classifying wheat diseases, as evidenced by the relatively small difference between the training and validation metrics.

ResNet50 emerged as the top-performing model, recording a training loss of 0.1106 and an accuracy of 0.9630. Its validation loss and accuracy were 0.1147 and 0.9649, respectively. A visual representation of loss versus epochs and accuracy versus epochs for ResNet50 would reveal the model's progressive improvement, characterized by a decline in loss and an increase in accuracy as the number of epochs grew**. [Fig.1, Fig.2].**

VGG19 also demonstrated a respectable performance, with a training loss of 0.5207 and an accuracy of 0.8234. The validation loss and accuracy were 0.5443 and 0.8231, respectively. By plotting the loss versus validation loss and accuracy versus validation accuracy per epoch for VGG19, the model's performance trends over time become evident. The figures would showcase the convergence of loss and accuracy metrics as the number of time periods expanded, so did the size of the training and validation sets**. [Fig.3,Fig.4]**

The three DL models exhibited varying degrees of success in detecting and classifying wheat diseases. ResNet50 outshone DenseNet121 and VGG19, achieving the highest accuracy and lowest loss metrics among the three. The graphical representation of loss and accuracy versus epochs for ResNet50 and VGG19 offers a deeper understanding of each model's learning trajectory and convergence behavior. These findings underscore the potential of DL techniques, particularly ResNet50, to revolutionize wheat disease detection and classification, ultimately contributing to improved agricultural Sustainability.



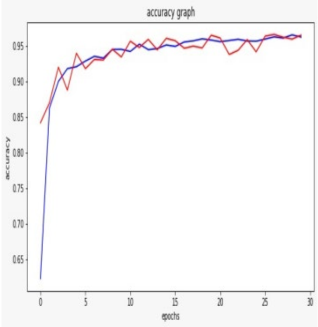
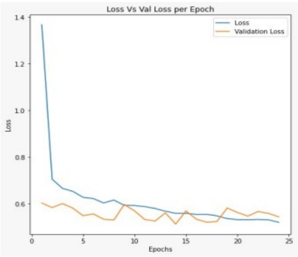


Fig.2 Loss vs Epochs **Fig.3** Accuracy vs Epochs



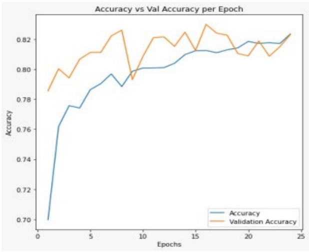


Fig.4 Loss vs Val Per Epochs **Fig.5 Accuracy** vs Val Per Accuracy

5. Result

The results of the comparative analysis of the three deep learning models, DenseNet121, ResNet50, and VGG19, provide valuable insights into their respective performances in detecting and classifying wheat diseases. By evaluating these models based on key metrics such as loss, accuracy, and area under the curve (AUC), we can identify their strengths and limitations in addressing this critical agricultural challenge. DenseNet121 exhibited a robust performance with a training loss of 1.0320, an AUC of 0.8870 (88.7%), and a validation loss of 1.1158. The model's AUC for the validation set was 0.8787 (87.87%), suggesting that DenseNet121 can effectively detect and classify wheat diseases with a high degree of accuracy. ResNet50 outperformed the other models, achieving a training loss of 0.1106 and an impressive accuracy of 96.30%. The model's validation loss was 0.1147, with a validation accuracy of 96.49%. This exceptional performance demonstrates the ability of ResNet50 to accurately detect and classify various wheat diseases. VGG19 also demonstrated a solid performance, with a training loss of 0.5207 and an accuracy of 82.34%. The model's validation loss was 0.5443, and its validation accuracy was 82.31%. Although VGG19 did not perform as well as the other two models, it still exhibits potential for detecting and classifying wheat diseases. By analyzing the loss and accuracy per epoch for each model, it is possible to gain a better understanding of their respective learning processes. For VGG19 and ResNet50, the provided figures illustrate the trends in loss and accuracy over time, offering valuable insights into their convergence rates and the stability of their training processes. In summary, the results indicate that ResNet50 demonstrates the best performance among the three models, followed closely by DenseNet121, with VGG19 offering a relatively lower but still acceptable level of accuracy.

6. Conclusion and Future Work

Addressing the identification and classification of yellow rust disease in wheat is of utmost importance due to its significant influence on global wheat production. Yellow rust, a result of the fungus Puccinia striiformis, impacts both the quality and quantity of wheat, leading to considerable economic losses for farmers and disrupting the worldwide availability of this essential staple crop. Yellow rust disease must be identified and classified as soon as possible are crucial for facilitating timely intervention and efficient disease management, which can help to alleviate the detrimental effects of the disease on crop yields, food security, and overall agricultural sustainability. This research explored the application of DL techniques, specifically DenseNet121, ResNet50, and VGG19, for detecting and classifying yellow rust disease in wheat. Through the comparative analysis of these models, we found that ResNet50 outperformed the other models, achieving impressive accuracy in detecting and classifying wheat diseases. DenseNet121 also demonstrated robust performance, while VGG19 offered a relatively lower, but still acceptable level of accuracy. The utilization of such deep learning models offers an innovative

approach to tackling the challenges posed by yellow rust disease in wheat. By employing advanced techniques like convolutional neural networks (CNNs), these models can automate the detection and classification process, making it more efficient and less reliant on human expertise. This, in turn, can lead to more effective disease management strategies and help minimize the economic and agricultural impacts of yellow rust disease on wheat production worldwide. Future research in this domain may focus on further refining and improving the performance of these models, as well as exploring other DL architectures that could potentially offer even better detection and classification accuracy. Additionally, incorporating other data sources, such as weather data and geographical information, may contribute to enhancing the overall effectiveness of these models in detecting and managing yellow rust disease in wheat. These approaches can effectively fuse limited labeled data with abundant time series information, thereby enhancing the accuracy and robustness of the detection models.

References

[1] Welling's, C. R. (2011). Global status of stripe rust: a review of historical and current threats. Euphytica, 179(1), 129–141. https://doi.org/10.1007/s10681-011-0360-y.

[2] Chen, X. . (2005). Epidemiology and control of stripe rust [Puccinia striiformis f. sp. tritici] on wheat. Canadian Journal of Plant Pathology, 27(3), 314–337. https://doi.org/10.1080/07060660509507230.

[3] Beddow, J. M., Pardey, P. G., Chai, Y., Hurley, T. M., Kriticos, D. J., Braun, H.-J., Park, R. F., Cuddy, W. S., & Yonow, T. (2015). Research investment implications of shifts in the global geography of wheat stripe rust. Nature Plants, 1(10), 15132–15132. https://doi.org/10.1038/nplants.2015.132.

[4] Chen, X. . (2007). Challenges and solutions for stripe rust control in the United States. Australian Journal of Agricultural

Research, 58(6), 648–655. https://doi.org/10.1071/AR07045
[5] McIntosh, R. A., Wellings, C. R., & Park, R. F. (1995). Wheat Rusts. CSIRO Publishing.
[6] 6.Benoit, G. (2018). Hinton, LeCun, Bengio : la « conspiration » du deep learning. Echos (Paris, France).
[7] 7.Snekhalatha, U., & Anburajan, M. (2012). Dual tree wavelet transform based watershed algorithm for image segmentation in hand radiographs of arthritis patients and classification using BPN neural network. 2012 World Congress on Information and Communication Technologies, 448–452. https://doi.org/10.1109/WICT.2012.6409119.
[8] Yurttakal, A. H., Erbay, H., İkizceli, T., Karaçavuş, S., & Biçer, C. (2022). Diagnosing breast cancer tumors using stacked ensemble model. Journal of Intelligent & Fuzzy Systems, 42(1), 77–85. https://doi.org/10.3233/JIFS-219176
[9] Fiona, J. R., & Anitha, J. (2019). Automated Detection of Plant diseases and Crop Analysis in Agriculture using Image Processing Techniques: A Survey. 2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT), 1–5. https://doi.org/10.1109/ICECCT.2019.8869316.
[10] SARDOĞAN, M., ÖZEN, Y., & TUNCER, A. (2020). Detection of Apple Leaf Diseases using Faster R-CNN. Düzce Üniversitesi Bilim Ve Teknoloji Dergisi (Online), 8(1),1110–1117. https://doi.org/10.29130/dubited.648387
[11] Sardogan, M., Tuncer, A., & Ozen, Y. (2018). Plant Leaf Disease Detection and Classification Based on CNN with LVQ Algorithm. 2018 3rd International Conference on Computer Science and Engineering (UBMK), 382–385. https://doi.org/10.1109/UBMK.2018.8566635
[12] Wang, M., Fu, B., Fan, J., Wang, Y., Zhang, L., & Xia, C. (2023). Sweet potato leaf detection in a natural scene based on faster R-CNN with a visual attention mechanism and DIoU-NMS. Ecological Informatics, 73, 101931. https://doi.org/10.1016/j.ecoinf.2022.101931
[13] Indian Applicants File Patent Application for Crop Disease, Disease Severity and Pests Detection Using Convolution Neural Network and Automatic Notification System to Increase Agricultural Productivity. (2019). Athena Information Solutions Pvt. Ltd.
[14] Zhang, Z., Flores, P., Friskop, A., Liu, Z., Igathinathane, C., Han, X., Kim, H. J., Jahan, N., Mathew, J., & Shreya, S. (2022). Enhancing Wheat Disease Diagnosis in a Greenhouse Using Image Deep Features and Parallel Feature Fusion. Frontiers in Plant Science, 13, 834447–834447. https://doi.org/10.3389/fpls.2022.834447
[15] Zhang, X., Han, L., Dong, Y., Shi, Y., Huang, W., Han, L., González-Moreno, P., Ma, H., Ye, H., & Sobeih, T. (2019). A Deep Learning-Based Approach for Automated Yellow Rust Disease Detection from High-Resolution Hyperspectral UAV Images. Remote Sensing (Basel, Switzerland), 11(13), 1554. https://doi.org/10.3390/rs11131554.
[16] Heaton, J. (2018). Ian Goodfellow, Yoshua Bengio, and Aaron Courville: Deep learning [Review of Ian Goodfellow, Yoshua Bengio, and Aaron Courville: Deep learning]. Genetic Programming and Evolvable Machines, 19(1-2), 305–307. Springer. https://doi.org/10.1007/s10710-017-9314-z.
[17] Krizhevsky, A., Sutskever, I., & Hinton, G. (2017). ImageNet classification with deep convolutional neural networks. Communications of the ACM, 60(6), 84–90. https://doi.org/10.1145/3065386
[18] 19.Mi Z, Zhang X, Su J, Han D, Su B. Wheat Stripe Rust Grading by Deep Learning With Attention Mechanism and Images From Mobile Devices. Front Plant Sci. 2020 Sep 9;11:558126. doi: 10.3389/fpls.2020.558126. PMID: 33013976; PMCID: PMC7509068.
[19] Mi, Z., Zhang, X., Su, J., Han, D., & Su, B. (2020). Wheat Stripe Rust Grading by Deep Learning With Attention Mechanism and Images From Mobile Devices. Frontiers in Plant Science, 11, 558126–558126. https://doi.org/10.3389/fpls.2020.558126
[20] Remote Sensing; Findings from Manchester Metropolitan University in Remote Sensing Reported (A Deep Learning-Based Approach for Automated Yellow Rust Disease Detection from High-Resolution Hyperspectral UAV Images) (p. 524). (2019). NewsRx.
[21] D. Kumar and V. Kukreja, "An Instance Segmentation Approach for Wheat Yellow Rust Disease Recognition," 2021 International Conference on Decision Aid Sciences and Application (DASA), Sakheer, Bahrain, 2021, pp. 926-931, doi: 10.1109/DASA53625.2021.9682257.
[22] Koc, A., Odilbekov, F., Alamrani, M. et al. Predicting yellow rust in wheat breeding trials by proximal phenotyping and machine learning. Plant Methods 18, 30 (2022). https://doi.org/10.1186/s13007-022-00868-0.
[23] Zhao, G., Quan, L., Li, H., Feng, H., Li, S., Zhang, S., & Liu, R. (2021). Real-time recognition system of soybean seed full-surface defects based on deep learning. Computers and Electronics in Agriculture, 187, 106230. https://doi.org/10.1016/j.compag.2021.106230.
[24] LONG Jiehua, GUO Wenzhong, LIN Sen, WEN Chaowu, ZHANG Yu, & ZHAO Chunjiang. (2021). Strawberry Growth Period Recognition Method Under Greenhouse Environment Based on Improved YOLOv4. 3(4), 99–110. https://doi.org/10.12133/j.smartag.2021.3.4.202109-SA006.
[25] Su, J., Yi, D., Su, B., Mi, Z., Liu, C., Hu, X., Xu, X., Guo, L., & Chen, W.-H. (2021). Aerial Visual Perception in Smart Farming: Field Study of Wheat Yellow Rust Monitoring. IEEE Transactions on Industrial Informatics, 17(3), 2242–2249. https://doi.org/10.1109/TII.2020.2979237.
[26] Kodali, R. K., & Gudala, P. (2021). Tomato Plant Leaf Disease Detection using CNN. 2021 IEEE 9th Region 10 Humanitarian Technology Conference (R10-HTC), 1–5. https://doi.org/10.1109/R10-HTC53172.2021.9641655
[27] Gunarathna, M. M., & Rathnayaka, R. M. K. T. (2020). Experimental Determination of CNN Hyper-Parameters for Tomato Disease Detection using Leaf Images. 2020 2nd International Conference on Advancements in Computing (ICAC), 1, 464–469. https://doi.org/10.1109/ICAC51239.2020.9357284
[28] Seetharaman, K., & Mahendran, T. (2022). Leaf Disease Detection in Banana Plant using Gabor Extraction and Region-Based Convolution Neural Network (RCNN). Journal of the Institution of Engineers (India). Series A, Civil, Architectural, Environmental and Agricultural Engineering, 103(2), 501–507. https://doi.org/10.1007/s40030-022-00628-2
[29] Correa, E., Garcia, M., Grosso, G., Huamantoma, J., & Ipanaque, W. (2021). Design and Implementation of a CNN architecture to classify images of banana leaves with diseases. 2021 IEEE International Conference on Automation/XXIV Congress of the Chilean Association of Automatic Control (ICA-ACCA), 1–6. https://doi.org/10.1109/ICAACCA51523.2021.9465178.