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Awareness of Identification of Plant Leaf Diseases in Cotton Fields with the Applications of Image Processing Techniques

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***Abstract*— This study highlights the threat of crop diseases, especially in cotton, to food security in developing nations. Identifying similar-looking leaf diseases requires costly, time-consuming visual analysis by experts. Early diagnosis is crucial to boosting agricultural yields. An image processing system, combined with preprocessing techniques like augmentation, background elimination, and filtering, enhances disease detection. Texture and color-based feature extraction, along with SVM classification and ANN models, improve accuracy. Advanced technologies like image processing and machine learning enable early detection, precise health monitoring, and increased agricultural productivity.**

***Index Terms*— Image Processing, Agriculture, Artificial Intelligence, Machine Learning, Deep Learning.**

I. INTRODUCTION

India is reliant on agricultural production because it accounts for 18% of its GDP and has been a key contributor to economic growth. Ref. [4] Farmers choose crops based on factors such as soil type, cli-mate, and economic value. Rising populations, changing weather, and political instability have driven agricultural innovation, resulting in increased yields through advances in genetics and fertilisers. However, crop diseases remain a major threat to food security, particularly in developing nations, ow-ing to farmers' lack of awareness. The visual identification of similar-looking leaf diseases is challenging, requiring experts and constant monitoring, which is expensive, time-consuming, and unreliable. [1] Plant illnesses are a serious threat to agriculture because they result in large losses of crops and money. Precision plant health monitoring and early disease detection are possible using modern technology. Ref. [10] Cotton, known as "silver fiber", is vital for the clothing industry but is highly susceptible to various plant diseases. In Bangladesh, the growing textile industry's demand for cotton exceeds its domestic supply, requiring significant foreign exchange. Traditionally, experienced crop pathologists have identified diseases through visual inspection, which is time consuming, costly, and challenging. Cotton diseases like Bacterial Blight, Root Knot Nematode, Fusarium Wilt, Root Rot, Verticillium Wilt, and the newly identified rolling-leaf disease threaten its growth, emphasizing the need for efficient detection and management methods. Ref. [9] Cotton-related products are valued by nearly half of the global population, but cotton diseases severely impact productivity and quality. Real-time health monitoring is crucial, especially in hydroponics and intensive farming. Traditional disease diagnosis through expert evaluations is costly and impractical for large farms, particularly in developing nations.

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Advances in image processing and machine learning provide efficient alternatives, enabling large-scale monitoring and automated early detection of diseases, transforming agricultural practices.

(a) (b) (c) (d) (e) (f) (g) (h)

Figure 1: Example images of : (A) Aphid, (B) Bacterial blight, (C) Curl virus, (D) Fusarium wilt, (E) Target spot, (F) Powdery Mildew, (G) Army Womb, (H) Healthy leaf

The cotton disease photo collection includes field and internet-sourced images scaled to 32 × 32 reso-lution. Ref. [3] It comprises eight categories, including seven disease types (areolate mildew, bacterial blight, curl virus, fusarium wilt, target spot, verticillium wilt, and brown spot) and healthy leaves, with sample images illustrated in Fig 1.

II. Literature Survey

The study presented a bidirectional RNN-LSTM architecture for illness recognition, predicting climatic variable detection. [2] Time series forecasting aids in predicting cotton plant diseases, while ML algo-rithms classify leaf diseases using image preprocessing. An SVM classifier achieved 94% accuracy in diagnosing diseases like Alternaria leaf spot and bacterial blight.

[9] AI-based image processing enhances automated disease detection, improving crop supervision. [1] An IoT system with deep CNN models detects cotton plant diseases using sensor data and image augmentation. A novel deep learning model with grey wolf optimization improved efficiency. [11] Synthetic image segmentation identified leaf damage under real-world conditions.

[5] DL advancements improve plant disease classification accuracy. [17] Thermal imaging aids rapid crop disease detection with high accuracy. [18] ANN-based models identify diseases using preprocessed images but lack precise measurement details. [22] VGG19 with XGBoost and RF enhances plant disease detection and short-term voltage stability in deep learning.

III. Methodology

- Image Acquisition: This is the first step, where the image is captured or acquired from a sensor or camera. This section describes the type of sensor or imaging equipment used, the settings, and the con-ditions under which the images are captured (e.g. resolution, lighting, etc.).
- Image Restoration: This step involves improving the quality of the image by removing the noise or distortion that may have occurred during image acquisition. In a research context, various restoration techniques, such as deblurring, denoising, or correcting geometric distortions, might be discussed.
- Image Enhancement: Here, the enhancement is done in an attempt to make the image more visually appealing, or to make it suitable for analysis. Skills might include techniques such as contrast adjust-ment, brightness, or histogram equalisation.
- Image Segmentation: This process involves partitioning the image into useful zones, most com-monly with a view of separating objects of interest or zones of interest. Standard segmentation tech-niques which include thresholding, edge detection, or region basis segmentation, can be described.
- Feature Extraction: This actually follows the segmentation where vital characteristics of the picture (such as the texture, form, or colour data) are extracted. This is common in machine learning or com-puter vision models, where the features extracted are useful for (classification or analysis).
- Recognition/Interpretation: The extracted features from the previous stage are then subjected to further analyses to facilitate pattern recognition or to merely decipher the image data. This can be achieved through machine learning situations, pattern recognition algorithms, or even classification in the identification of objects, or tasks such as detection of diseases in plants.
- Image Compression: Optional in some systems but enhances this step involved the compression of the image size in the storage or transmission process, but with little effect on image quality.
- Image Encryption: If necessary, encryption techniques protect the image data from unauthorised access, especially in security-sensitive applications.

Fig. 3 is a bar graph representing the use of various machine learning methods in cotton plant leaf dis-ease detection research. The data show a higher use of more advanced methods such as Convolutional Neural Networks (CNN) compared to traditional methods such as Support Vector Machines (SVM) and K-nearest neighbours (KNN), reflecting trends in the field towards deep learning. Fig. 4 A bar graph of scientific production from 2015 to 2024 shows a gradual increase in published articles from 2015 to 2019, with a slight increase in 2020. Publications doubled in 2021 compared to 2019, likely driven by technological advancements and global challenges. In 2023, over 250 articles were published, reflect-ing growing researcher interest, advancements in specific fields, and the influence of global factors, such as COVID-19. This trend indicates higher planned scientific output post-2020, suggesting sus-tained investment in R&D. This highlights the increasing relevance of the field and situates the current study within the evolving literature.

The recommended approach entails assembling data from several foundations, including meteorologi-cal, soil, and satellite images. [6]. The collected data were processed and analysed to identify trends and patterns. Machine learning models, including regression, classification, and clustering, can be de-veloped to forecast cotton output and detect diseases in cotton plants. Ref. [2] developed a framework using refined deep learning models such as VGG-16, VGG-19, InceptionV3, and Xception for cotton leaf disease detection. These models require extensive training with a large dataset to achieve higher accuracy in disease detection. Ref. [14] A deep CNN model architecture was implemented using GWO. The values from the GWO method were first used to build a deep CNN model. We then utilised the dataset used to determine if cotton leaves have illnesses to train and test these deep networks. Ref. [17] The recommended approach de-livers high accuracy while minimising the parameters. The cotton dataset was created using Custom CNN, VGG16, ResNet50, and the meta learning method. The CNN model contains a max-pooling layer, dropout layer, and five convolutional layers. Ref. [18] suggested automated systems that focus on ma-chine and deep learning techniques. They used a variety of datasets, some of which were openly acces-sible and others of which were created in real time. Systems based on deep learning outperformed those based on machine learning. Ref. [15] Utilizing qualitative or quantitative data, design science builds and assesses a methodology that specifies concepts, practices, technological capabilities, and products and generates innovations. A model, or conceptual representation and abstraction of datasets, is one of the outcomes of the DSRM. Ref. [13] TL and ResNet101 were used to identify cotton leaf dis-eases, focusing on Areolate Mildew, Myrothecium leaf spot, and soreshine. Owing to an initially insuf-ficient dataset, the DAg method was employed to expand it. ResNet101 processed the enhanced dataset for feature extraction, followed by training with various ratios (80/20, 70/30, and 50/50). A serial-based approach combines features from different layers, with a Genetic Algorithm (GA) optimising the most prominent features for final recognition using a Cubic SVM. Ref. [10] CNN architecture is uti-lised to automatically identify important features in images without human intervention. Its ability to share parameters and reduce dimensionality allows it to efficiently apply learned information across different areas of the image, requiring less processing power. To identify sick cotton plants and leaves, the features extracted using CNN methods such as padding, strides, and pooling were trained using augmented image data. Ref. [9] The pre-activation residual module and the residual module with bot-tlenecks each have two branches. In the residual module with a bottleneck, one branch connects direct-ly to the output, whereas the other combines outputs after a sequence of CONV, BN, and RELU layers. The pre-activation residual module adds RELU to the output, improving the training by following a flow of BN, RELU, and CONV three times instead of using RELU.

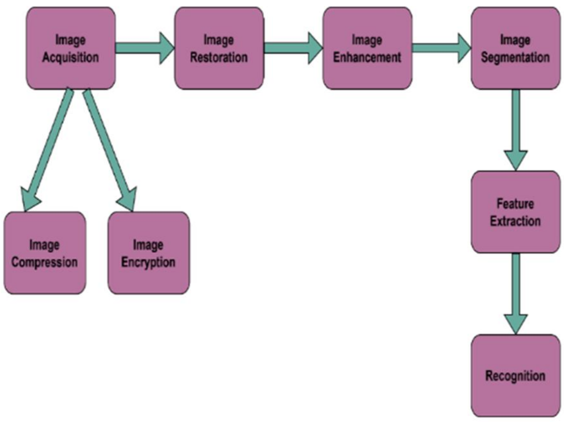

Figure 2: Basic Steps for plant illness discovery and classification in image processing

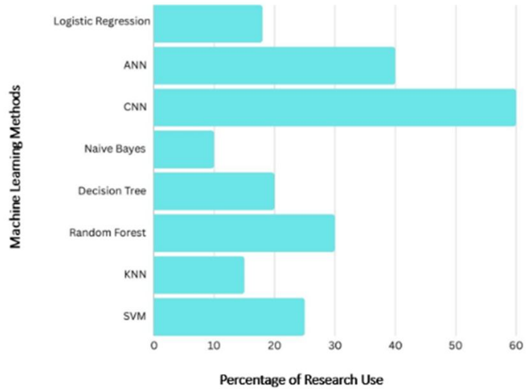

Figure 3: Use of Machine Learning Methods in Cotton Plant Leaf Disease Detection Research

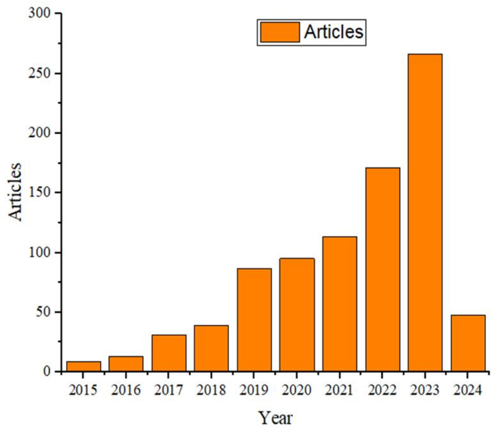

Figure 4: Annual Scientific production

A comparison of various studies using algorithms, accuracy, and their limitations is presented in Table 1.

TABLE I: LITERATURE SURVEY REVIEW

S.no	Ref.No	Algorithm	Accuracy	Limitations
1	[1]	Convolutional Neural Network (CNN) Support Vector Machine (SVM) Image Processing Techniques	96.67%	1)Generalization of Unseen Data. 2)Requirement for Specialized Hardware or Technical Knowledge. 3)Dependency on High-Quality Images.
2	[2]	SVM (Support Vector Machine) Multilayer Perceptron (MLP) Artificial Neural Network (ANN) KNN (K-Nearest Neighbors)	98.70 %	1)Class Imbalance 2)Adaptability to Novel Diseases 3)Feature Extraction and Selection 4)Real-Life Deployment Challenges
3	[3]	Pruning algorithm and transfer learning strategies:VGG16 ResNet164 DenseNet40	 90.77% 96.31% 97.23%	1)Model Generalization 2)Resource Constraints 3)Comparison with Other Methods 4)Long-term Sustainability
4	[4]	RESNET Algorithm	97%	1)Limited Scope of Disease Detection 2)Dataset Specificity 3)Model Complexity and Resource Requirements 4) Lack of Real-Time Implementation 5) Evaluation Metrics
5	[8]	Support Vector Machine (SVM) Grey Wolf Optimization (GWO)	91.2%	1)Specific Cotton Variety 2) Disease Levels Focus 3) Future Expansion Needed 4) Cost of Hyperspectral Instruments
6	[10]	CNN and Transfer learning	95%	1)Dependence on High-Quality Data 2) Generalization Across Different Conditions 3) Computational Resources

7	[11]	Traditional K-Means Algorithm	99.5%	1) Limited Disease Detection 2) Dependence on Image Quality 3) Processing Time 4) Manual Intervention
8	[12]	Convolutional Neural Networks (CNNs) Artificial Neural Networks (ANN) Hybrid Neuro-Fuzzy Networks (NFC) Support Vector Machines (SVM) Closest k-Neighbors (KNN)	80.30%	1) Unbalanced Data 2) High Cost and Low Availability of Data 3) Noise in Manual Classification 4) Generalization to Other Crops
9	[13]	Genetic Algorithm Cubic SVM (Support Vector Machine)	98.8%	1) Dataset Size and Diversity 2) Model Generalization 3) Computational Resources 4) Expert Involvement in Dataset Preparation
10	[14]	Grey Wolf Optimization (GWO)	98.36%	1) Agricultural Application Challenges 2) Hyperparameter Tuning 3) Environmental Factors
11	[17]	Convolutional Neural Networks (CNNs)	98.53%	1)Mobile Deployment Challenges 2) Generalization Across Different Crops 3) Dataset Limitations
12	[20]	Pretrained Convolutional Neural Networks (CNNs)	96.38%	1) Data Dependency 2) Computational Resources 3) Environmental Variability 4)Specificity to Cotton 5) Adaptation Over Time

IV. CONCLUSION

This study uses Artificial Neural Networks (ANN) and thermal imaging for early cotton leaf disease detection, improving identification accuracy. Thermal imaging enables fast detection of temperature variations, while Machine Learning (ML) and Deep Learning (DL) enhance disease analysis. ANN pro-cessing of leaf images improves detection, though precise growth rate data is crucial. Advanced tools like thermal imaging, ML, and ANN are essential for early disease detection and better crop manage-ment, requiring further research for refinement.

REFERENCES

[1] Sharvesh, S., Kumar, S., Raman, C. J. (2024). Accurate plant disease detection technique using machine learning. EAI Endorsed Transactions on Internet of Things, 10. https://doi.org/10.4108/eetiot.4963

[2] Islam, M. M., Talukder, M. A., Sarker, M. R. A., Uddin, M. A., Akhter, A., Sharmin, S., Mamun, M. S. A., & Debnath, S. K. (2023). Deep learning model for cotton disease prediction using fine-tuning with smart web application in agriculture. Intelligent Systems with Applications, 20(200278), 200278. https://doi.org/10.1016/j.iswa.2023.200278

[3] Zhu, D., Feng, Q., Zhang, J., & Yang, W. (2022). Cotton disease identification method based on prun-ing. Frontiers in Plant Science, 13. https://doi.org/10.3389/fpls.2022.1038791

[4] Kant, S. A., Pavani, M., & Kumar, K. K. (2022). Cotton leaf disease detection and prediction using ResNet algorithm. Journal Of Harbin Institute of Technology, 54(11), 49-57.

[5] Saha, P. & Nachappa, M. N. (2022). Cotton Plant Disease Prediction Using Deep Learning. International Journal for Research in Applied Science & Engineering Technology, 10(3), 744-746.

[6] International Journal for Research in Applied Science & Engineering Technology (IJRASET) ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538 Volume 11 Issue VI Jun 2023- Available at www.ijraset.com

[7] Saha, P. & Nachappa, M. N. Deploy Cotton Plant Disease Prediction Application using CNN and Flask.

[8] Zhang, N., Zhang, X., Shang, P., Ma, R., Yuan, X., Li, L., & Bai, T. (2023). Detection of cotton Verticilli-um wilt disease severity based on hyperspectrum and GWO-SVM. Remote Sensing, 15(13), 3373. https://doi.org/10.3390/rs15133373

[9] Rajasekar, V., Venu, K., Jena, S. R., Varthini, R. J., & Ishwarya, S. (2021). Detection of Cotton Plant dis-eases using deep transfer learning. Journal of Mobile Multimedia. https://doi.org/10.13052/jmm1550-4646.1828

[10] Ahmed, M. R., & Department of Computer Science and Engineering, Stamford University Bangladesh, Dhaka-1217, Bangladesh. (2021). Leveraging convolutional neural network and transfer learning for Cot-ton Plant and leaf disease recognition. International Journal of Image Graphics and Signal Pro-cessing, 13(4), 47–62. https://doi.org/10.5815/ijigsp.2021.04.04

[11] Odukoya, O. H., Aina, S., & Dégbéssé, F. W. (2023). A Model for Detecting Fungal Diseases in Cotton Cultivation using Segmentation and Machine Learning Approaches. International Journal of Advanced Computer Science and Applications, 14(1).

[12] Ahmed, M. R., & Department of Computer Science and Engineering, Stamford University Bangladesh, Dhaka-1217, Bangladesh. (2021). Leveraging convolutional neural network and transfer learning for Cot-ton Plant and leaf disease

recognition. International Journal of Image Graphics and Signal Pro-cessing, 13(4), 47–62. https://doi.org/10.5815/ijigsp.2021.04.04

[13] Rizwan Latif, M., Attique Khan, M., Younus Javed, M., Masood, H., Tariq, U., Nam, Y., & Kadry, S. (2021). Cotton leaf disease recognition using deep learning and genetic algorithms. Computers, Materials & Continua, 69(3), 2917–2932. https://doi.org/10.32604/cmc.2021.017364

[14] Gülmez, B. (2023). A novel deep learning model with the grey wolf optimisation algorithm for cotton dis-ease detection. Journal of Universal Computer Science, J. UCS, 29(6), 595–626. https://doi.org/10.3897/jucs.94183

[15] Azath, Zekiwos, M., & Bruck, A. (2021). Deep learning-based image processing for cotton leaf disease and pest diagnosis. Journal of Electrical and Computer Engineering, 2021, 1–10. https://doi.org/10.1155/2021/9981437

[16] Kumar, S., Ratan, R., & Desai, J. V. (2022). Cotton disease detection using the TensorFlow machine learn-ing technique. Advances in Multimedia, 2022, 1–10. https://doi.org/10.1155/2022/1812025

[17] Memon, M. S., Kumar, P., & Iqbal, R. (2022). Meta deep learn leaf disease identification model for cotton crop. Computers, 11(7), 102. https://doi.org/10.3390/computers11070102

[18] Idrees, M. F., Qadir, M., Alam, M., & Farid, S. (2022). Novel-Based Deep Learning Approach for Early Diagnosis of Cotton Crop Disease. Journal of Information Communication Technologies and Robotic Ap-plications, 13(1), 1-07.

[19] Hassan, S. M., Amitab, K., Jasinski, M., Leonowicz, Z., Jasinska, E., Novak, T., & Maji, A. K. (2022). A survey on the detection of different plant diseases using machine learning techniques. Electronics, 11(17), 2641. https://doi.org/10.3390/electronics11172641

[20] Raj, M. M. P., Vijayakumar, J., Prakash, A. H., & Hemalatha, A. (2024). A Deep Learning Solution for Early Detection of Cotton Nutrient Deficiencies. Journal of Systems Engineering and Electronics (ISSN NO: 1671-1793), 34(6).

[21] Rodriguez-Sanchez, J., Li, C., & Paterson, A. H. (2022). Cotton yield estimation from aerial imagery using machine-learning approaches. Frontiers in Plant Science, 13. https://doi.org/10.3389/fpls.2022.870181

[22] Hassan, S. M., Jasinski, M., Leonowicz, Z., Jasinska, E., & Maji, A. K. (2021). Plant disease identification using shallow convolutional neural network. Agronomy (Basel, Switzerland), 11(12), 2388. https://doi.org/10.3390/agronomy11122388

[23] Singh, V., Sharma, N., & Singh, S. (2020). Review of imaging techniques for plant disease detec-tion. Artificial Intelligence in Agriculture, 4, 229–242. https://doi.org/10.1016/j.aiia.2020.10.002