Journal of Positive School Psychology
2022, Vol. 6, No. 3, 6227–6233 http://journalppw.com

Design and development of a robust Deep learning model for detection of disease cotton crop

Dr. Anita Keshav Patil
Professor & Head , Department of Electronics and Telecommunication Engineering, Dr.Vithalrao Vikhe Patil College of Engineering, Ahmednagar, Maharashtra 414111, India, anitamdhoke@gmail.com

Abstract
A deep learning model to identify damage to cotton leaves is proposed in this work, which is based on photographs of cotton harvesting in the field. Deep learning models are used to identify damage to cotton leaves. Cotton is one of the most profitable horticultural crops in the world, and it has been cultivated in virtually every part of the planet. It has become the focus of a wide range of farming nuisances and diseases in tropical climates, prompting the deployment of efficient control methods in these regions. Additionally, it is difficult for the creator to distinguish between the affects of the primary nuisances and diseases in the underlying stages, making it tough for them to locate the proper identifying proof of a harm in the underlying stages. The current work gives an answer based on significant expertise in the screening of cotton leaves, which allows for improved monitoring of the health of the cotton crop and the ability to make better judgments regarding its management. With the use of convolutional neural networks, two convolutional brain models — GoogleNet and Resnet50 — achieved accuracy rates of 86.6 percent and 89.2 percent, respectively, in their classifications. This approach outperforms standard methods for managing pictures, such as support vector machines (SVM), closest k-neighbors (KNN), imitating brain organisations, and neuro-fluffy, by a factor of 25. (NFC). This means that this strategy may be able to contribute to a more speedy and accurate analysis of the plants that are populating the area in the future.
Keywords: Image processing, and precision agriculture**,** Artificial intelligence, convolutional neural networks.

INTRODUCTION

The production of normal strands of cotton has the potential to be the most profitable crop on the planet[1,] especially in developing countries. More than a quarter of the world's arable area is dedicated to its cultivation [2], which is a significant amount. [3] According to official Brazilian government figures, a total of 28.2 million tonnes of cotton were gathered from 17 million hectares of land during the 2019/2020 growing season. Both Mato Grosso and Bahia, which are hot and humid regions, are the places where the majority of Brazil's growth is focused, despite the country's small size. Ramularia leaf spot, a parasitic disease, develops in these locations as a result of a combination of high development and significant capital expenditure in mechanical infrastructure. The ramularia infection is one of the most prevalent diseases seen on cotton plantations all over the world [5,6]. With ramulose, alternaria spot, and parasites, it has a substantial influence on the Brazilian cotton crop, resulting in reductions in the usefulness, fibre, and seed qualities

[7]. A number of distinctive aspects of cotton farming in humid tropical climates are present, including the existence of a broad variety of pests and illnesses that need continual attention to detail [8-10]. It has been shown that using insecticides, acaricides, and fungicides in a preventive way is the most efficient method of controlling disease-carrying bugs and parasites [4,11]. Nevertheless, according to studies, the insufficient and unexpected usage of such items has increased the prevalence of irritations and infections in rural regions [12,13]. .. For cotton growers, the conversation shifts from organic concerns to financial ones because the need for rehashed uses of such items and dose expansions has increased the cost of production to the point where pesticide consumption has exceeded half the cost of production for three seasons in a row [14]. The use of such items should be restricted to more affordable and serious creation [15,16], with the exception of those utilised to control nuisances and agricultural illnesses, which everyone agrees on logical grounds. According to Ghaffar et al. [17], cotton production may be increased while yet remaining manageable. Accurate developments in farming technology may be able to make this reality. By addressing efficiency guidelines and soil fruitfulness, monitoring by satellite and robots, and even prohibiting the use of specific substances [18],

it is possible to achieve a decrease in pesticide usage of more than half [18].

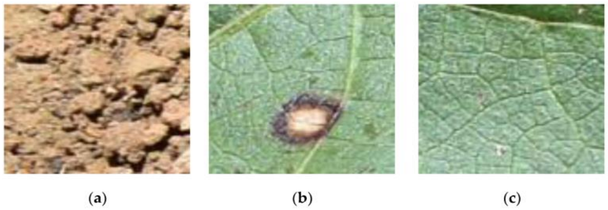

Figure 1. Examples of images of (a) background (soil), (b) lesioned leaf, and (c) healthy leaf.

[19] The capacity to change the quality of horticulture crops is a critical component of the regulated management of these crops. Cotton producers have limited access to geospatial assessments of disease dispersion because of the need for alternative preventative pesticide applications to combat diseases that are difficult to manage, as well as a lack of equipment to improve the approach associated with planning in the field [5,11]. Recently, it has been increasingly common to conduct research using remote detection and robotics to prepare for rural nuisances and diseases. However, despite the important logical advancements that have been made, these technologies still face social and financial limitations in terms of their use. When it comes to projects involving Integrated Pest and Disease Management, the use of agrochemicals, whether administered randomly or at variable rates, is still the most important instrument accessible to the board of directors of a ranch (MIPD).

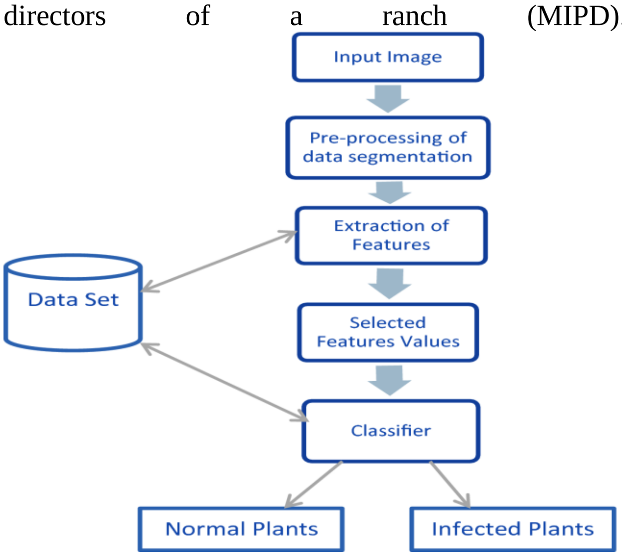

Figure 2. Conventional Cotton crop plant leaf disease identification methods

Unlike conventional counterfeit brain organisations, convolutional brain networks address a development in conventional counterfeit brain organisations since the input is displayed as an ordered progression with various degrees of deliberation. When these techniques are meticulously created, the classification of samples becomes extremely exact and precise. It is CNN's structure that has the most influence when it comes to extracting and merging components from a photograph. Results by Abade et al. [27] show that CNNs may be used to identify plant ailments, and that the accuracy is reasonable even when a huge quantity of information is collected from photos taken in the field. A study conducted by Barbedo [30] found that utilising leaf sores and spots combined with deep learning algorithms for different harvests, it was feasible to diagnose plant illnesses with an accuracy of more than 70% for a variety of harvests. In their research, Deebe and Amuthe [31] used various convolutional brain network designs to obtain accuracy ranging from 62 to 96 percent. However, they came to the conclusion that the organisations perform better for a collection of existing controlled data, because the accuracy decreased for information gathered under genuine field conditions. The use of CNNs in the diagnosis and identification of agricultural illnesses is deemed helpful by Boulent and colleagues [32] because they are able to cope with the difficulties of a wide range of pictures that are difficult to decipher and interpret.

The following is the continuation of the paper on page two: Classical machine learning algorithms as well as deep convolutional neural networks are addressed in Section 2 of this document. The proposed CNN model for identifying cotton crop leaf disseas is described in depth in Section Three. Afterwards, in Section 5, the findings are summarised and examined in further depth with regard to the research questions.

I. RELATED WORK

A number of different representations of the schematic convolutional brain architecture are shown in Figure 13. Consequently, it was able to predict four distinct types of engine imaginaries using the identical electro encephalography data as the original experiment. By transitioning from a 2D to a 3D point of view, they were able to better organise their data. The management of the structure was the responsibility of these stacked components. The use of transient voltage soundness, according to a review [14], was advised for leveraging the particular path of deep learning. By attaining a steady momentary voltage, it was determined to utilise the bunching calculation to improve the unshakable quality of the system by increasing the unshakable quality. In order to diagnose mango tree leaf diseases, according to [7], a deep learning technique was applied. More than 1,200 mango leaf records from five different mango leaf diseases were analysed by the researchers. ' In order to develop the CNN framework, around 600 photos were used, with 80 percent being used for preparation and 20 percent being used for testing. For the purpose of precisely tracking down and identifying mango leaf diseases, 600 photos were employed. The results indicated the possibility of using this technology in ongoing applications. When there are more pictures in the dataset, it is feasible to fine-tune the limitations of the CNN model, resulting in an increase in the 'e order accuracy. According to the study review [6, rice plant datasets are utilised to identify and characterise the CNN model, which is trained on the data. Over 500 distinct photos of diseases from the rice exploration field were collected for use in the preparation process. ' In [15], the arrangement of cotton leaves was attended to with the application of picture handling. By utilising K-implies calculations, it is possible to segment the datasets. 'e research [16] found the illnesses that cause the leaves of banana trees to become tainted. There were a total of 3700 photographs utilised in the preparation for this test review, however there is no similar dataset for each of the four categories. Using coloured and grayscale photo datasets, for example, scientists evaluated the preparation procedure. They also looked into alternate dataset partition strategies, such as averaging. Their shaded picture accuracy was 98.6 percent, and they were able to produce the approval dataset with accuracy of 80 percent and 20 percent, respectively, using the shaded picture accuracy.

1.1. Aims and limitations of the study are discussed in Section

The goal of this project is to construct a different proof model for cotton leaf diseases and nuisances, which will be implemented using a deep learning method known as convolutional brain organisation. A number of frequent diseases and pests, including the bacterial curse, the leaf excavator, and the insect bug, have had a negative impact on the efficiency and quality of cotton. The model also created a controlled learning approach on datasets with four major component extraction procedures and 2400 datasets, according to the researchers. In e datasets, there are only four element descriptors that may be used to describe the elements. Because of time restrictions and the proximity to cotton-producing areas, the research concentrated on the southern section of Ethiopia, which included Arba Minch, Shele, and Woyto. MelkaWorer horticulture exploration community, which is responsible for cotton ranches in SNNPR and was regarded a core region, was also included in the list of core regions. For the purpose of carrying out the pre-programmed data deletion, advanced learning algorithms were used.

II. PROPOSED METHODOLOGY

The sample leaf photographs that the scientists have used in this investigation are both necessary and optional types of datasets, according to the researchers. Essential information is a type of knowledge that has been obtained in a novel and engaging way. The essential sorts for this review were gathered from July to August 2021 from India cotton ranches, where cotton plants are commonly planted and there is high contamination in SNNPR; however, optional information for each class was gathered from rural exploration places established in the India area and SNNPR. As part of this evaluation, the analyst used purposive or critical evaluating procedures, selecting three contaminated and one solid case from the general population, which was not selected using a probability distribution. When collecting information, 2400 photos of information are captured and classified into four equal types, such as bacterial scourge, sound, leaf excavator, and insect parasite. These pictures of information are then utilised to build an adjusted dataset, as shown in Figure 3.

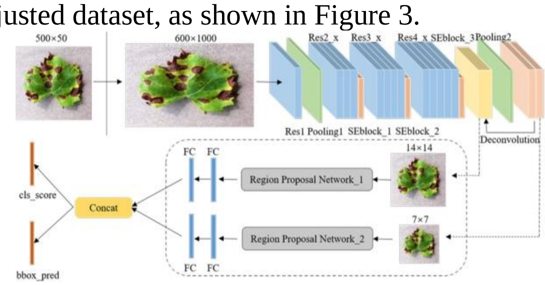

Figure 3. Proposed model of this work

2.1. Cotton Images' Sample Digitization

In order to obtain clear, unbiased images of leaves in the cotton plant test data set for further inquiry and management, the information acquisition framework was used in this investigation. As part of the digitization process, the goal was to provide the framework with a consistent lighting or brightness adjustment. They are captured using a mobile phone camera and then transferred to a PC, where they are seen on a screen and saved to the hard drive as advanced shading images.

2.2. Image Data Preprocessing

Integrating pre-processed photographs into an organisation is, first and foremost, a critical component of any picture-handling activity. Aspects of photo handling projects that include vectorization, standardisation, image resizing, and picture growth are among the most prevalent preparatory activities. These tasks are completed in this investigation before delving into the more in-depth handling of the OpenCV library in Python [18], which will be discussed later. In addition, data expansion is used to generate extra preparation datasets from the original data sets in order to conduct data sampling from them.

2.3. Feature Extraction

Profound learning solves many shortcomings of artificial intelligence highlight extraction, such as physically eliminating highlights by employing the most effective and powerful approach available, known as a CNN [19]. 'e layers are employed in order to become more familiar with the content. By utilising a separating instrument, information may be used to match and concentrate their attributes in order to improve their overall performance.

Dataset Partitioning and Model Selection Methodology

The majority of the time, CNNs operate by performing a variety of convolutions at various layers of the network. A variety of representations of how knowledge is organised may be created, beginning with the most generic in the fundamental layers and progressing to more particular representations in the deeper layers [41]. As a result of the reduction in the dimensionality of the input information, the convolutional layers function as a sort of attribute extractor in some situations. Layers in the convolutional levels that are more discriminative are being developed, with middle-of-the-road layers separated by revised direct units (ReLU) and more discriminative layers in the convolutional layers (pooling). Traditional descriptions of how convolutional layers function make use of channels that transition from one input picture to another in order to describe how they work [42]. Towards the conclusion of the organisation, the last properties of the picture are highlighted, resulting in the final step (layer) being a straightforward classification algorithm.

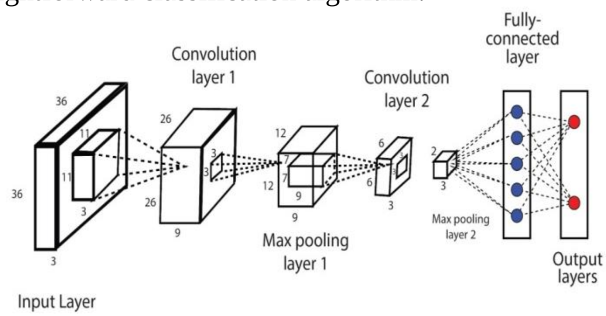

Figure 4. Improved CNN architecture

2.4. Tool Selection

The photographs of cotton leaves for this inquiry were taken using a mobile phone and a high-end camera, respectively. It was necessary to utilise Python version 3.7.3 for the purposes of this model. A similar approach to that used by Keras, the model is developed on top of TensorFlow 2.2.4-tf, which is an integral element of the Keras deep learning framework. TensorFlow is recommended for use with the framework in version 1.14.0 or higher. A graphical user interface (GUI) based on the Tkinter library was used to conduct a series of assessments. CPU-based preparation and testing were used instead of graphics processing units (GPU).

2.5. Evaluation Techniques

Analysts employed a number of methodologies to determine if the design was practicable at various phases, including the formative phase and at the conclusion of the project. The experts first review the disarray network acquisitions and four evaluation metrics for framework reports, including the F1-score, Precision, Recall, and Accuracy, on the test dataset, before proceeding to the next step. When it came to emotional assessment, a poll was employed in this study, as shown in Figures 3 and 4, to gauge how people felt about a model provided by space scientists. The exploratory investigation was carried out in order to offer an objective appraisal of a curio collection piece. The conclusion of the examination ultimately shows the model's materiality and its connection to the world.

III. RESULTS AND DISCUSSION

The ultimate outcome is produced by employing boundaries to partition the model's display, such as a K-crease cross-approval with ten folds, to create the desired result. With an increase in the RGB-shaded picture dataset, the model performs 15 percent better, according to the results. They employed the grayscale dataset, as well as the moved learning CNN model, in order to get an accuracy rate of 98.6 percent [6,] according to the experts. Before a model can use a coloured dataset, a significant amount of the day must be spent preparing it for execution. However, shading is a key and extremely definite component in the identification and classification of cotton. When it comes to providing support for a model presentation, figures such as the age with 100 cycles and the Adam streamlining approach are essential. A CNN algorithm has been taught to properly recognise 98 percent of diseases, 94 percent of noises, 97 percent arachnid vermin, and 100 percent of leaf minors at this point in time, according to researchers. Various preprocessing techniques have been employed by the scientist in the course of commotion evacuation. There are three primary reasons for the misclassification of the results: the bacterial plague, solid, and leaf excavator are the main offenders. On cotton plants, the model's accuracy in identifying leaf disease and vermin is plainly evident in the disorderly grid, indicating that the model is 96.4 percent accurate.

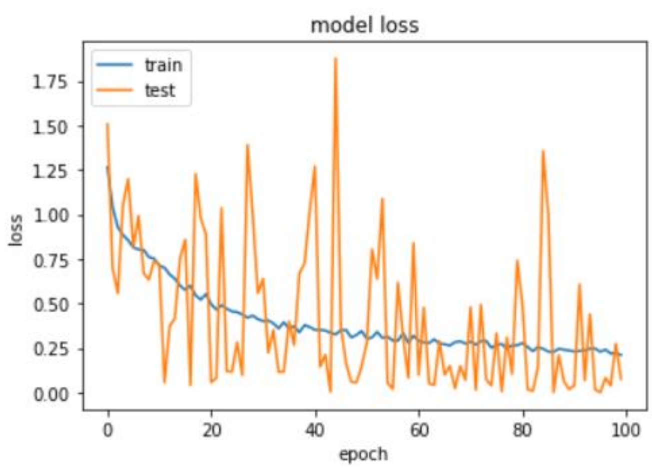

Figure 5. Cotton Leaf crop disease identification

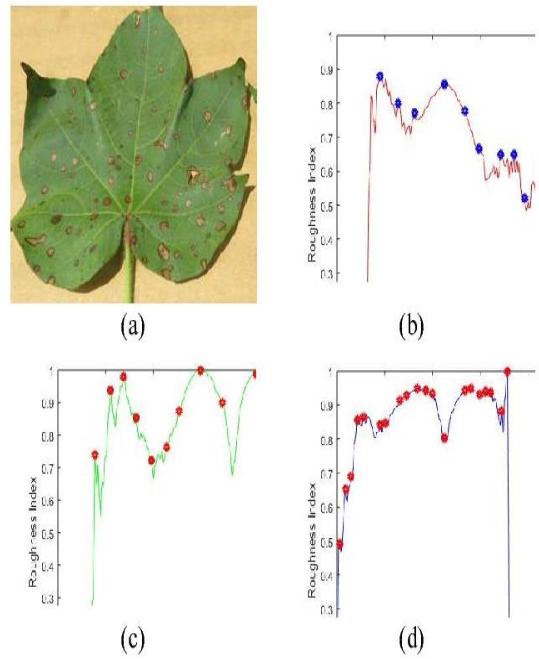

Figure 6. (a) Cotton Leaf (b) plot roughness measure obtained for red, (c) and (d) are ROC for training and testing

Table 1:Accuracy of Cotton Leaf Disease Detection

Name of Disease	Correctly Classified (CC)	Incorrectly Classified (IC)	Accuracy of CC
Bacterial Blight	67	11	85.89%
Alternaria	55	10	84.61%
Cerespora	39	08	82.97%
Grey Mildew	31	06	83.78%
Fusarium Wilt	28	06	82.35%
Healthy leaf	08	02	80%

Since the pictures were caught under field conditions, i.e., without any control of lighting and openness, as well as of being from the yields of various years and with various types of sores, it is accepted that the outcomes got here demonstrate the possibility of CNN calculations for the discovery leaf sores in the cotton crop. In any case, Stallkamp et al. [80] recommend that in uses of AI it is essential to test calculations with new information and in various circumstances, for example, with pictures of different harvests, wet leaves, and gravely sustained plants. Such new tests ought to make it conceivable to decide the heartiness and limit of reflection of the technique created.

IV. CONCLUSION

Applying cotton leaf sores as an example, this paper provides a great introduction to using deep learning for the identification of cotton leaf sores, proving that it can be used to definitively identify agricultural pests and illnesses. Deep convolutional networks have been used to replace the normal picture processing in the typical pipeline with two different models of deep convolutional networks. One of the most significant advantages of utilising deep learning to learn new models is an increase in overall accuracy. Furthermore, it has been demonstrated that the modification of information is a critical component of high-performance operations. In spite of the fact that the findings of the ResNet50 convolutional network were higher in terms of general assessment and correlation between classes, the typical gap between its results and those of GoogleNet is immaterial from a specialised point of view. Because of the robustness of convolutional brain organisations, we believe that the current results can be applied to functional devices in a practical setting. Field photography was used to capture the images included in this book. A selection of the photographs was combed through in order to zero down on the ones that were important. This photo collection was the sole source of information that enabled us to arrive at these conclusions.

REFERENCES:

[1] Ethiopian Institute of Agricultural Research, Cotton Research Strategy, EIAR, Addis Ababa, Ethiopia, 2017.
[2] P. Sonal, P. Patil, M. Rupali, and S. Zambre, “Classification of cotton leaf spot disease using support vector machine,” International Journal of Engineering Research and Applications, vol. 4, no. 5, pp. 92-93, 2014.
[3] O.-I. e. Inga Hilbert, “'e cotton supply chain in Ethiopia,” Freiburg, vol. 38, 2018.
[4] B. S. Prajapati, V. K. Dabhi, and H. B. Prajapati, “A survey on detection and classification of cotton leaf disease,” in Proceedings of International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT), pp. 1-2, Chennai, India, March 2016.
[5] A. R. Hevner, S. T. March, J. Park, and S. Ram, “Design Science in IS Research,” Management Information, vol. 28, pp. 75–105, 2004.
[6] S. Arivazhagan and S. VinethLigi, “Mango leaf diseases identification using convolutional neural network,” International Journal of Pure and Applied Mathematics, vol. 120, pp. 11067–11079, 2018.
[7] L. Yang, S. Yi, N. Zeng, Y. Liu, and Y. Zhang, “Identification of rice diseases using deep convolutional neural networks,” Neurocomputing, vol. 276, no. 1, pp. 378–384, 2017.
[8] S. Wallelign, M. Polceanu, and C. Buche, “Soybean plant disease identification using convolutional neural network,” in Proceedings of Artificial Intelligence Research Society Conference, Melbourne, FL, USA, May 2018.
[9] Y. Hou, S. Jia, S. Zhang et al., “Deep feature mining via attention-based BiLSTM-GCN for human motor imagery recognition,” arXiv preprint arXiv:2005.00777, 2020.
[10] M. A. Schwemmer, N. D. Skomrock, P. B. Sederberg et al., “Meeting brain-computer interface user performance expectations using a deep neural network decoding framework,” Nature Medicine, vol. 24, no. 11, pp. 1669–1676, 2018.
[11] Y. Hou and S. Jia, “Deep feature mining via attention based BiLSTM-GCN for human motor imagery recognition,” Journal of LATEX Class Files, vol. 14, no. 8, 2020.
[12] X. Lun, S. Jia, Y. Hou et al., “GCNs-net: a graph convolutional neural network approach for decoding time-resolved eeg motor imagery signals,” arXiv preprint arXiv:2006.08924, 2020.
[13] S. Jia, Y. Hou, Y. Shi et al., “Attention-based graph ResNet for motor intent detection from raw EEG signals,” arXiv preprint arXiv:2007.13484, 2020.
[14] M. Zhang, J. Li, Y. Li, and R. Xu, “Deep learning for short term voltage stability assessment of power system,” IEEE Access, vol. 99, 2021.
[15] D. S. R. G. Pawan and P. Warne, “Detection of diseases on cotton leaves using K-mean clustering method,” International Research Journal of Engineering and Technology, vol. 2, no. 4, pp. 426–428, 2015.
[16] J. Amara, B. Bouaziz, and A. Algergawy, “A deep learningbased approach for banana leaf diseases classification,” in Proceedings of Datenbanksysteme f¨ur Business, Technologie und Web (BTW 2017), pp. 80–89, Stuttgart, Germany, March 2017.
[17] Y. Lyu, J. Chen, and Z. Song, “Image-based process monitoring using deep learning framework,”

Chemometrics and Intelligent Laboratory Systems, vol. 189, pp. 7–19, 2019.
[18] Z. Ni, Y.-X. Cai, Y.-Y. Wang, Y.-T. Tian, X.-L. Wang, and B. Badami, “Skin cancer diagnosis based on optimized convolutional neural network,” Artificial Intelligence in Medicine, vol. 102, pp. 1–7, 2020.
[19] F. Chollet, Deep Learning with python, pp. 138–141, Manning Publications Co., Shelter Island, NY, USA, 2018.
[20] T. Guo, J. Dong, H. Li, and Y. Gao, “Simple convolutional neural network on image classification,” in Proceedings of IEEE International Conference in Big Data Analysis, pp. 721–730, Boston, MA, USA, December 2017.