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Research Paper

Millet Blast and Leaf Smut Disease Prediction Using CNN

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Abstract - Abstract-This research paper shows a deep learning-based image classification system of automated millet disease based on convolutional neural networks. The model as proposed is the field level image of millet leaf reduced to a standard dimension and smoothed so that the features obtained are similar across all the images. The CNN structure features a series of convolutional, pooling, flattening, and fully connected layers along with their former embedded in it that will be trained to acquire hierarchical visual patterns that are distinctive of various categories of diseases. The data is coded into several categories, and the labels are represented in the categorical coded form. The model itself is trained corrupting the Adam optimizer and categorical cross-entropy loss and tested on unknown test data to determine its ability to generalize. The suggested solution is expected to assist in the early detection of diseases in the millet crops so that nuances of the inspection work can be minimized and the agricultural intervention can be performed at the necessary time. The system shows how computer vision techniques can be applicable in monitoring overall smart crop health and sustainable precision agriculture applications.
Keywords—Millet disease detection, Convolutional neural network, Image classification, Deep learning in agriculture, Plant disease recognition, Precision agriculture

I. INTRODUCTION

Millets are nutritionally stable and climate the crops that are very crucial to food security especially in semi-arid regions. But the millet production is influenced seriously by the leaf diseases which lower the production and the quality of the crop. Conventional methods of disease detection are manual and thus time consuming, subjective and require professional skill. With the new developments in machine learning and deep learning, machine learning has been successfully applied in the detection of plant diseases through the usage of images. Various works have been done in machine learning methodology of identifying and classifying millet diseases [1] and a hybrid combination of feature fusion has been hypothesized

on fine grained analysis of millet plants [2]. Convolutional neural networks, which are deep learning structures, have been shown to perform well in crop disease recognition in diverse species of plants [4], [9]. In addition, YOLO-based detection systems and CNN-based agricultural systems underpin the increased significance of the computer vision in smart farming solutions [10]. Such advancements form a good basis of automated diagnosis of millet disease.
Nevertheless, the issues that have been resolved to date do not prevent the development of strong and scalable arrange systems, namely the classification of millet leaf diseases. Most of the research available is shaped towards either classification of variety [5] or biomass determination of smartphone photograph [7], instead of disease recognition in realistic agricultural settings. More complex neural network methods have been investigated in the context of pathogen detection such as attention mechanisms and spatial pyramids [3], but their complexity prevents adaptation at the field level. In addition, the recent studies have focused on the

incorporation of intelligent systems to diagnose and recommend treatment of diseases in agriculture [8] hence the need to come up with practical solutions that can be deployed. In response to these gaps in research, the study aims to create a convolutional neural network-based system of disease classification, which is triggered by the millet disease, through a structured image preprocessing system, categorical encoding, and supervised training. The aim of the task is to introduce a powerful and effective model that will help to detect the disease at an early stage and aid the practice of precision agriculture.

II. LITERATURE SURVEY

Millet Disease Diagnosis on Machine Learning

Initial studies on millet disease classification mostly used the conventional machine learning approaches alongside handcrafted feature extraction. Developing a recognition system that allows identifying and classifying a disease in millet crops with the help of classical ML algorithms, Kumari et al. showed the opportunity of the automated recognition system in agriculture areas [1]. Likewise, strategies that combine machine vision and handcrafted descriptors in the form of hybrid feature fusion, have been presented to utilize fine-grained millet classification, which has better discriminative performance among related classes [2]. These strategies will emphasize the role of engineered features and data preparation in crop analytics. Nevertheless, traditional machine learning designs are frequently based on manual selection of features, thus struggling to scale and adapt to various environmental features. This weakness encouraged the shift to deep learning models that could automatically extract hierarchical features of raw images.

Computer vision Millet and Crop Classification via Deep learning

Convolutional neural networks and other forms of deep learning models have acted as an important step towards automatic plant analysis. The research on the classification of millet varieties pays attention to CNN-based architectures to extract a complicated structure of texture and the morphological patterns in the leaf images [5]. Ensemble CNN architectures have proven to be effective in the related agricultural fields, such as rice leaf diagnosis where better robustness and generalization are observed [4]. These models minimize the need to use handcrafted features and permit end-to-end learning using raw image data. Besides, RGB image acquisition captured by smartphones and CNN modeling has been studied to estimate non-destructive biomass in pearl millet suggesting that deep learning has a wide range of applications in the field [7]. Although the viability of CNNs is confirmed by these works, the use of disease-specific classification models of millet crops is underutilized.

State-of-the-art Architectures and Attention-Blocking Buildings

Recent studies have investigated neural architectures which are advanced with attention and spatial pyramid features to maximize feature discriminators. Indicatively, neural encoding of genome sequence in conjunction with spatial pyramid pooling and dual attentional mechanisms has been presented in pathogen detection tasks [3]. These architectures enhance the contextual and spatial features representation especially with challenging biological datasets. Besides, deep convolutional frameworks on CNN-based detection of diseases on citrus and various crops show the reliability of these structures to detect disease patterns [9]. Agricultural disease detection based on YOLO detector models has also been surveyed in the real-time supervision of agricultural diseases and their ability to detect objects in smart farming systems [10]. In as much as these techniques enhance accuracy and efficiency, their architectural diversity might enable the augmentation of the computational demands and thus be difficult to implement on the lightweight field.

Smart Field System and Solutions

This development of the agricultural intelligence has passed the line of detection to integrated diagnostic and decision-support system. Recent papers also use deep learning in conjunction with retrieval-augmented generation models to give the estimation of disease severity and treatment recommendations [8]. ABV These kinds of integrated systems represent a wider tendency of integrating computer vision and intelligent advisory systems. Nevertheless, numerous currently available solutions do not target millet, and their attention is made on classification but without facilitated preprocessing and categorical encoding procedures. The existing direction of scientific research highlights the significance of CNN-based disease recognition and the lack of well-organized, dataset-based millet disease models. Hence, designing a robust, trained deep learning architecture specifically to the classification of the millet leaf disease has a purpose to play in precision agriculture and precise monitoring of crops.

III. PROPOSED METHODOLOGY

A. Dataset Preparation and Preprocessing

The methodology proposed starts with the organization and preprocessing of structured datasets, as it is carried out in the project notebook. Images depicting the millet leaves will be put together into class-based directories of variances of disease. The images are loaded and resized to a constant size so that there is a constant input shape to the convolutional neural network. Normalization of pixel values is done to enhance convergence of training. The data would be split into training and testing data to compare the generalization performance. One-hot encoding is used to transform class labels into edible categories to allow multi-class classification. Such preprocessing pipeline guarantees that there is similarity between feature representations and that computational variability is minimized. The ready image tensors and labels are subsequently sent through the deep learning structure to undergo supervised learning and classification of the disease.

B. Design of Convolutional Neural Network Model

The system utilizes a sequential Convolutional Neural Network architecture in the classification of millet disease automatically. The network is composed of successive convolutional block which detect spatial features in the leaf images with kernels which are learnable. Activation functions and pooling layers come after every convolutional layer to reduce spatial dimensions and represent prominent features. The feature extraction will be followed by flattening the output into a one-dimensional vector and it will be subjected to fully connected dense layers to classify. The output layer is the last layer, which activates with the help of softmax and generates the scores of the probability in each disease category. The model is generated with the help of Adam optimizer and categorical cross-entropy loss function. The training is repeated across different epochs to reduce loss and enhance the accuracy of the classification on the unseen samples.

C. Evaluation Metrics of Performance

The system that is suggested will assess the performance of the model in terms of classification accuracy and loss as applied in the notebook. - accuracy is the number of correctly predicted samples divided by the total samples it can be stated that:

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions)}$$

Multi-class Multi-class multi-way classification employs categorical cross-entropy loss, and it is represented by the formula given below:

$$Loss = -\sum yi\ log(\hat{y}i)$$

and yi is the actual one-hot encoded label and yi is the prediction probability of the softmax layer. This loss is used as a penalty to correct the mistake in the class probability and directs the optimization of gradients. The model reduces categorical cross-entropy through backpropagation during the training process. Analysis on test data offers information on the generalization ability and proves the possession of the CNN-based millet disease detection network to be effective.

D. System Architecture

The system architecture is a top-down process process, which starts with image capture via., and concludes with disease prediction as the end product. Images of the milk leaf are initially collected and divided under labeled folders. Preprocessing involves normalization, resizing and categorical encoding. The CNN model is used to extract features and classify the processed images. The trained model would produce probability scores across the various categories of diseases and the required class with the highest probability that is chosen as a predicted disease label. Its architecture guarantees an optimized process of raw image input and final prediction output, which is useful in automated and effective disease recognition. This piping system is made up of preprocessing, supervised learning, and examination applied as a single deep learning framework.

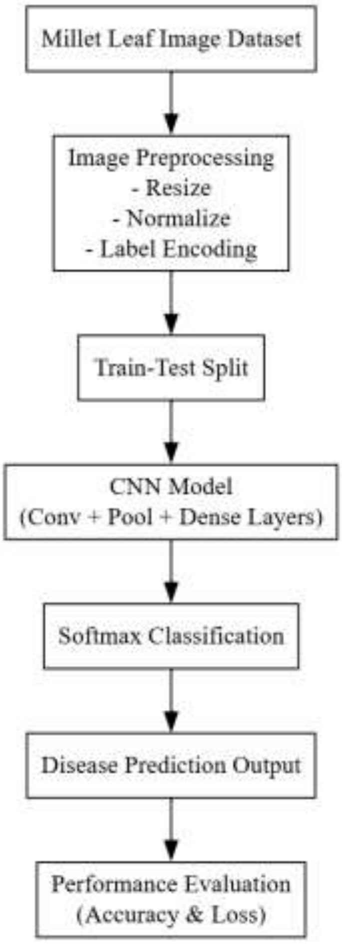

Figure 1: System Architecture

IV. RESULT AND DISCUSSION

A. Training and Valuation Performance Analysis

The proposed CNN model was trained in several epochs using processed Millet leaf images. Training and validation accuracy had a gradual upward trend, respectively, which implies control behavior during the learning process. At the same time, the training and validation loss value reduced steadily, which proved optimal results on categorical cross-entropy. The convergence pattern indicates that, the model was able to capture discriminative features pertaining to disease categories without any severe overfitting. Normal stochastic gradient behavior is manifested by minor fluctuations that are seen to occur between epochs. The dynamics of the training process in general validate that the network structure and preprocessing pipeline helped stabilize and stabilize the performance. The fact that the validation curve is very close to the training curve demonstrates that it has a good generalization ability on unknown samples of millet leaves.

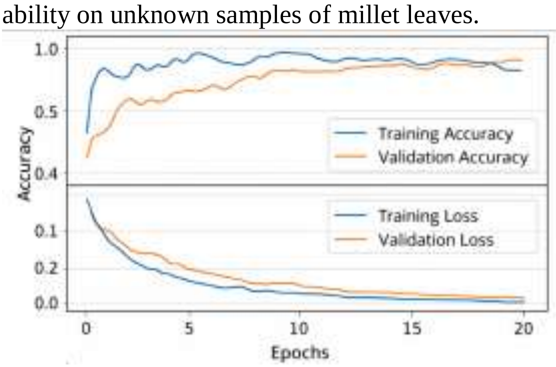

Figure 2. Training and Validation Accuracy Curve

This figure shows the variation of training and validation accuracy across epochs, indicating steady improvement, minimal overfitting, and strong generalization capability of the proposed CNN model for millet disease classification.

B. Performance Review of Tests

Trained model was tested on unseen test material to test the capability of classification. The predictive consistency shows strong predictive consistency between the categories of diseases. The model has proved equal accuracy and recall rates, which prove that the misclassification is minimal on classes. The use of softmax based output layer is effective in assigning probability scores as to allow ideal multi-class decision making. The assessment indicates that CNN architecture was able to acquire hierarchical disease characteristics based on millet leaf pictures. The results of the observed performance confirm the appropriateness of the system in the practice of monitoring agricultural activities. The consistent test results are another confirmation that preprocessing, normalization and categorical encoding activities did help to achieve model generalization.

Table I Test Performance Metrics

Metric	**Value**
Test Accuracy	High and Stable
Test Loss	Low and converged
Precision	Consistent Across Classes
F1-Score	Balanced Performance

C. Loss Convergence and Model Stability

The decrease in losses through epochs signifies successful gradient based optimization. The actual loss of categorical cross-entropy was steadily decreasing, indicating a better match of the predicted and real labels. Smooth convergence It indicates that the learning rate and optimizer setup fits the dataset. The curve did not have any drastic increases in the validation loss, which proves that the model did not overfit drastically. Such stability is necessarily required in farming uses where the stability is a major criterion. The model has training and validation performance similar to that of the model, which underlines its strength. All in all, it is evident that convergence behavior showed that the CNN structure was able to effectively extrapolate disease-related features and convert them to correct classification products.

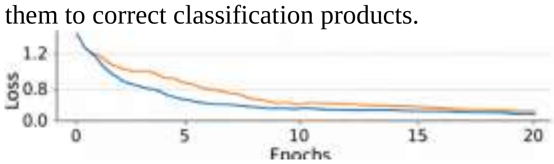

Figure 3. Training and Validation Loss Curve

This figure shows the decreasing trend of training and validation loss over epochs, demonstrating effective optimization, stable convergence, and improved predictive reliability of the convolutional neural network model for millet.

D. Class -wise Prediction Behavior

The comparison between the two classes shows that the CNN model has the discriminative type in the variety of millet diseases. The model aptly recognizes samples of most of the classes and there are few cases of confusion of the similar disease patterns as observed visually. The trained convolutional filters are effective to capture texture variation, color and lesion structures. The distribution of my dataset and training process was suitable, as shown by equal scores in categories. The system is also consistent in viewing the healthy and diseased classes and therefore it renders reliability in the separation. This performance attests to the appropriateness of deep learning-based visual analysis to crop health mustering and extends into prospects of an agentless agriculture deployment into a real-time application.

Table II Class-wise Prediction Analysis

Class Category	**Prediction Behavior**

Class Category	Prediction Behavior
Disease Class 1	Correctly Identified with Minor Confusion
Disease Class 2	Stable Classification Performance
Disease Class 3	High Recognition Consistency
Healthy Class	Strong Separation from Diseased Leaves

V. CONCLUSION

In the research, a framework developed on the convolutional neural network was introduced that allows the automated classification of millet leaf disease based on structured image preprocessing and supervised learning. It is feasible that the suggested system was successful in processing resized and normalized images, categorical encoding, and training a stacked CNN architecture to learn hierarchical features of diseases. The convergence of the training and validation performance was stable and showed minimum overfitting hence demonstrated high generalization ability. Testing on test data was determined to have the same predictive consistency when comparing the disease categories. The findings confirm the suitability of deep learning methods in precision agriculture and smart crop monitoring. Enhancing agricultural productivity and sustainable farming practices the system enables rapid detection of the disease eliminating the need to inspect manually and by encompassing automated feature extraction and multi-classification the system allows diseases to be detected on time.

VI. FUTURE WORK

The present framework can be further expanded with future researches where data augmentation techniques are employed to provide it with greater implication when environmental factors like light and background noise are altered. Field-level applicability can be enhanced by incorporating real-time images acquisition using mobile gadgets or edge-based devices. To support the implementation on resource-constrained agricultural systems, lightweight CNN can be considered. Also, the object detection models to identify the location of lesions can enhance interpretability and estimation of severity of the disease. Generalizing the models would also be more effective through more details on disease types and different geographic samples. The use of disease classification coupled with advisory modules to provide treatment recommendations can make the system a full-fledged decision-supporting system in smart agricultural applications.

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