ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24OCT252

Potato and Maize Plant Disease Detection Using Leaf Images

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Abstract:- Plant diseases represent a serious threat to national productivity and global food security. Effective therapy for multiple diseases requires a precise and useful differentiation of them. In this work, a computerized system for the identification and categorization of diseases in potato and maize crops is developed using convolutional neural networks. The demonstration was created with the ResNet50V2 model and tested on a combined collection of images of leaves. The system achieved an astounding accuracy of 85.19. Enhancing model execution through exchange learning, fine-tuning, and information augmentation were all part of the process. With the use of another dataset, the trained model was verified and produced positive results, almost exactly differentiating between the disease-causing leaf type (potato or maize). This technology helps ranchers adopt sustainable and knowledgeable disease management methods by promoting timely mediations, which in turn advances disease discovery.

Keywords:- *Potato, Maize, Leaf Disease, Machine Learning, CNN Model.*

I. INTRODUCTION

The timely and correct identification of plant diseases is vital for the development of effective control methods, as they pose a serious danger to both agricultural output and global food security. Manual expert assessments, which can be time-consuming, subjective, and prone to error, are a major component of traditional approaches for diagnosing these disorders. Machine learning methods, in particular Convolutional Neural Networks (CNNs), have demonstrated potential in automating the diagnosis and categorization of plant diseases in order to tackle these issues. The goal of this research is to create a machine learning framework that can recognize plant diseases from photos of leaves. In particular, the framework will differentiate any sickness shown and discriminate between clears out from potato plants and maize. There are several advantages to such a structure. First, it can significantly improve the efficiency and adaptability of sickness diagnosis, enabling timely interventions and reducing unfortunate events. Additionally, it can assist farmers and agricultural specialists in making informed decisions on disease management practices, leading to more sustainable and environmentally friendly practices [1]. Additionally, the framework can aid in the development of early warning systems, enabling preventative actions against disease outbreaks [2].

II. BACKGROUND STUDY

Over time, researchers have looked at using machine learning techniques, especially deep learning models like Convolutional Neural Systems (CNNs), for automated detection and diagnosis of plant diseases. In order to achieve an accuracy of 99.35%, Mohanty et al. (2016) demonstrated the capacity of deep CNN models in identifying 14 trim illnesses [3]. Furthermore, Sladojevic et al. (2016) achieved an accuracy of 96.3% in identifying 13 illnesses in apple takes off by using a deep CNN [4]. In order to detect cassava disease, Ramcharan et al. (2017) produced a compelling CNN program that achieved 93 accuracies [5]. Additionally, CNNs have been used to treat certain trim infections. In order to identify bacterial spots in tomato takes off, Selvaraj et al. (2019) used a CNN demonstration, reporting a precision of 97.28% [6]. With a 91.2% accuracy rate, Brahimi et al. (2017) presented a CNN-based method for identifying diseases in date palms [7]. Furthermore, with a precision of 90.16%, Artzet et al. (2019) demonstrated the suitability of CNNs in the diagnosis of several illnesses in bananas [8]. Analysts have investigated alternative machine learning models for plant infection detection in addition to CNNs. With a 97.14% accuracy rate, Kour, and Arora (2020) used a Bolster Vector Machine (SVM) to diagnose diseases in pomegranate peels [9]. Arbitrary Timberlands was used by Coulibaly et al. (2019) to identify millet head infections, with a 93.2% accuracy rate [10]. Exchange learning techniques, such as fine-tuning CNN models that have already been trained on specific datasets, have also shown promise. Additionally, et al. (2019) improved

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24OCT252

the VGGNet demonstration to identify cassava diseases with an 88% accuracy rate [11]. With a 96.6% accuracy rate, Polder et al. (2019) used exchange learning with the InceptionV3 demonstration to diagnose tomato diseases [12]. Also, analysts investigated the use of spectroscopy and hyperspectral imaging for plant diseases. With a 95% accuracy rate, Nagasubramanian et al. (2019) identified charcoal ruin in soybean stems using hyperspectral imaging and machine learning [13]. Qin et al. (2019) achieved an accuracy of 90.6% in diagnosing diseases in wheat takes off by combining machine learning with visible and near-infrared spectroscopy [14]. Despite the encouraging results, there are still difficulties in developing robust and generalizable models that can manage various environmental factors, disease stages, and plant varieties [15]. Furthermore, a constraint continues to be the availability of large, annotated datasets [16]. Addressing these issues via fascinating partnerships and sophisticated data gathering techniques is crucial for further advancement in this area [17].

III. METHODOLOGY

A. Model:

The network used in this extension is a Convolutional Neural Network (CNN) constructed using the ResNet50V2 network, which was previously trained on the ImageNet dataset. The foundation model is the pre-trained ResNet50V2, with some of its layers unfrozen for fine-tuning, allowing the model to adapt to the specific task of plant disease location.

To create a unique CNN engineering that is appropriate for the task at hand, more layers are added to the best parts of the pre-trained display. These layers include group normalization and max pooling layers following a 2D convolutional layer with 1024 channels and a 3x3 kernel size. refined and strengthened at that moment, often resulting in a configuration of thick layers with 2048, 1024, and finally the yield layer, which has the number of units according to the number of classes in the dataset.

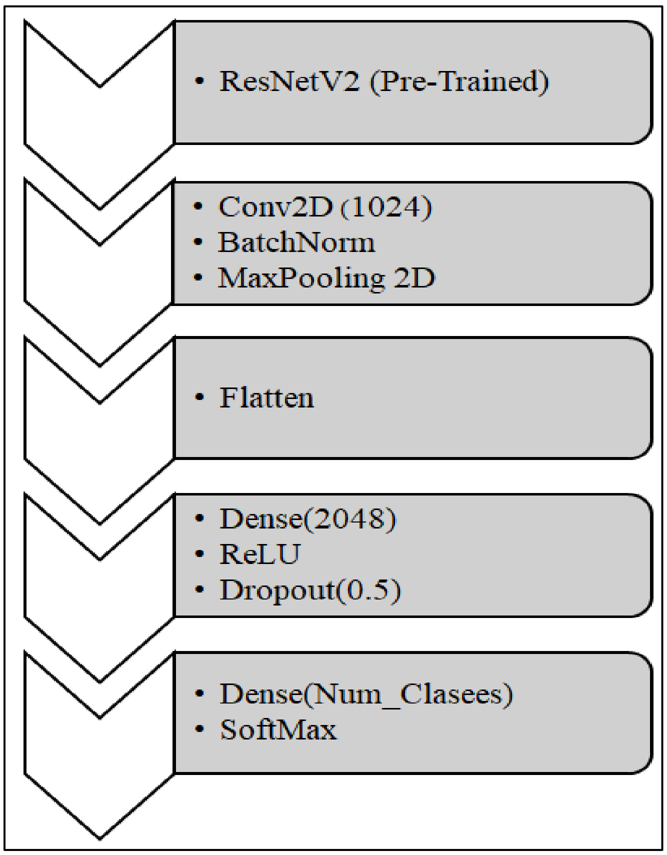

Fig.1. Neural Network Architecture

The example reduces dropout layers at a rate of 0.5 to prevent overfitting and advance generalization [18]. To provide lesson probabilities for each infection category, the last layer makes use of a SoftMax actuation work. During preparation, an Adam optimizer and categorical cross-entropy misfortune work are used to build the demonstration. The modified technique, which gives underrepresented classes more weights, is used to construct course weights to account for the difficult nature of the lessons within the dataset [19].Screening the approval precision and adjusting the learning rate in an analogous way are done by early stopping and learning rate lowering callbacks. The demonstration with the best approval accuracy is saved as the final one for later use.

Volume 9, Issue 10, October – 2024 International Journal of Innovative Science and Research Technology
ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24OCT252

B. Dataset:

The two publicly available datasets from Kaggle that are specifically selected to prepare a Convolutional Neural Network (CNN) demonstration to differentiate between diseases in potato and maize peels make up the combined dataset used in this extension. The amalgamation of these databases results in a complete resource that enhances the potency and accuracy of disease identification for these two crucial crops.

Fig. 2. Maize Leaf Images from Dataset

The dataset on maize (corn) leaf infection includes 4,188 images, divided into four distinct classes: Common Rust (1,306 images), Gray Leaf Spot (574 images), Curse (1,146 images), and Sound (1,162 images). Together with testing of solid clears out, this dataset provides a diverse range of instances pertaining to prevalent ailments affecting maize plants. The diversity of this dataset ensures that the program is exposed to a range of disease indicators, enhancing its symptomatic potential.

Fig. 3. Potato Leaf images from Dataset.

The dataset on potato leaf sickness is an enormous collection of 3,076 images taken in uncontrolled environments. This data set differs from many others that focus on controlled environments and contagious diseases since it provides a good portrayal of potato leaf infections encountered in actual agricultural settings. It includes the following seven basic classes: Phytophthora (347 photos), Infection (532 pictures), Nematode (68 pictures), Solid (201 pictures), Microscopic organisms (569 pictures), Organisms (748 pictures), Bug (611 photographs), and Nematode (68 pictures). A well-rounded dataset for demonstration preparation is ensured by the various characteristics of infection types, which are brought on by various pathogens like parasites, infections, troubles, microscopic organisms, Phytophthora, and nematodes, close to sound leaf tests. Combining these two datasets allows the project to achieve a comprehensive preparation set that addresses a variety of leaf diseases affecting maize and potato plants. A more complete picture of real-world situations is provided by this coordinated dataset, which covers prevalent infectious diseases and expands to include additional pathogen-induced disorders, annoyances, and natural components. A useful application in infection management and trim checking is made possible by the addition of solid leaf tests from both crops, which let the model distinguish between sick and healthy leaves. Additionally, adding images that were shot in uncontrolled environments with varying points, foundations, and distances adds more variables and complications. The model's generalization skills are improved by this changeability, which makes it far more appropriate for use in actual agricultural environments. The authenticity and distinctions added to this combined dataset are essential for developing robust and practical frameworks for infection discovery, which will aid in the effective management of illnesses and trim checks.

C. System Process:

The overall structure graphic provides a high-level schematic of the entire leaf disease detection process. The many steps are evident, starting from the input leaf photographs and ending with the final disease expectation. The graphic illustrates the preparation actions related to the input images, including downsizing and normalization, that were recently implemented to enhance them for the CNN program. The input images are formed, and expectations are raised by the CNN show, which is talked to by the show figure. Then, using the lesson titles, these expectations are translated to the comparison of leaf types and diseases.

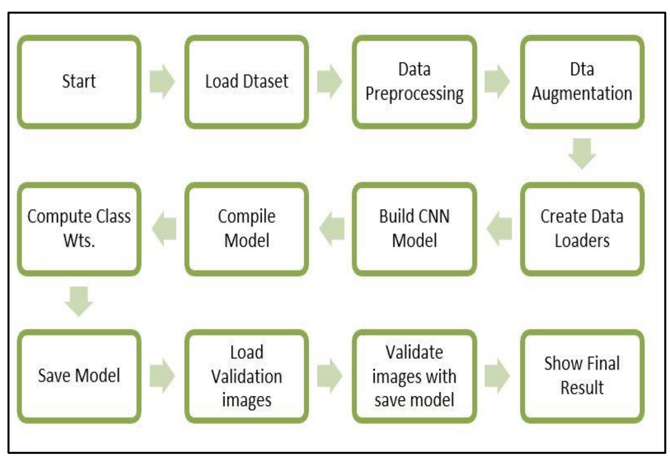

Fig. 4. Overall Structure of the Leaf Disease Detection System [20]

Volume 9, Issue 10, October – 2024 International Journal of Innovative Science and Research Technology
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D. Final Validation Process:

Using a collection of images of leaf illnesses gathered from Google, the analyst performed a final evaluation in order to support and authorize the implementation of the leaf disease location display. These images were chosen to speak to various leaf types, diseases, and visual traits. The images were not included in the original preparation or approval datasets. The gathered images were then processed and included into the planned CNN show, allowing the analyst to contrast the predictions made by the algorithm with the actual names. With valuable insights into the model's practical application and its ability to generalize to subtle data from a variety of sources, this last approval stage will help assess the model's efficacy and suitability in realistic situations.

IV. RESULT

Based on the ResNet50V2 design, the Convolutional Neural Arrange (CNN) framework that was put into hone performed well when it came to recognizing plant sicknesses from pictures of maize and potato takes off. The show illustrated its adequacy in recognizing between solid and wiped out clears out with a great precision of 85.19%, after being prepared on a differentiated dataset.

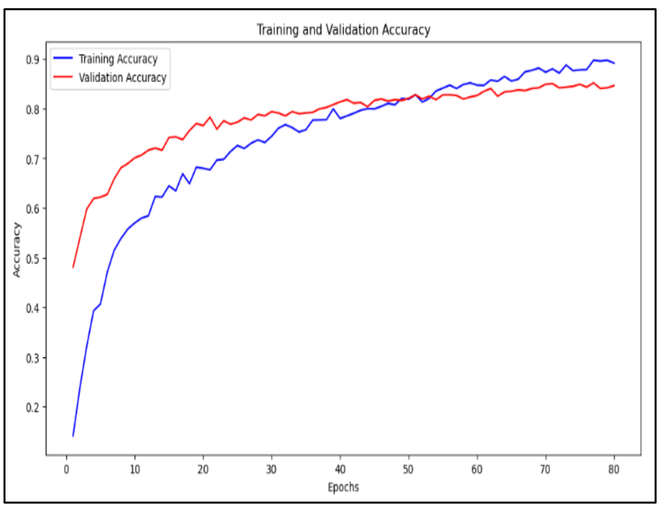

Fig. 5. Training And Validation Accuracy

The model viably learned and generalized from the given information, as prove by the steady diminish in both preparing and approval misfortunes over an 80-epoch period. At first, the demonstrate battled with the complexity of the assignment, as shown by its low early precision scores. In any case, as preparing advanced, the model's execution relentlessly progressed, highlighting its capacity to distinguish complex designs and highlights inside the leaf pictures. The preparing exactness come to 89.74%, demonstrating the model's capability in optimizing and fine-tuning parameters amid the preparing stage.

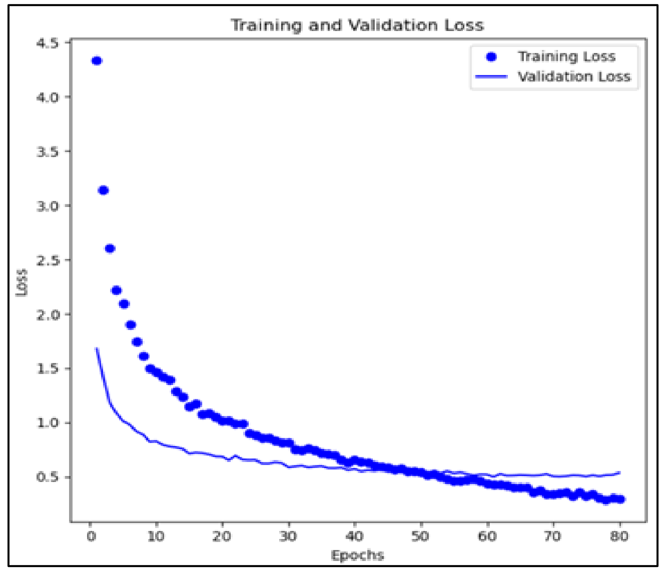

Fig. 6. Training and Validation Loss

The validation of the prepared show included employing an unmistakable approval dataset that was not utilized amid the preparing handle. This approval dataset was utilized to evaluate the model's strength and generalization capabilities. The approval exactness of 85.19% affirmed the model's capacity to generalize to already inconspicuous information. Furthermore, the model was approved employing a isolated dataset of pictures collected from Google. The demonstrate effectively recognized the leaf sort (maize or potato) and precisely distinguished the disease show within the pictures. This approval handle illustrated the model's unwavering quality and viability in real-world scenarios, where changed foundations, areas, and lighting conditions are common.

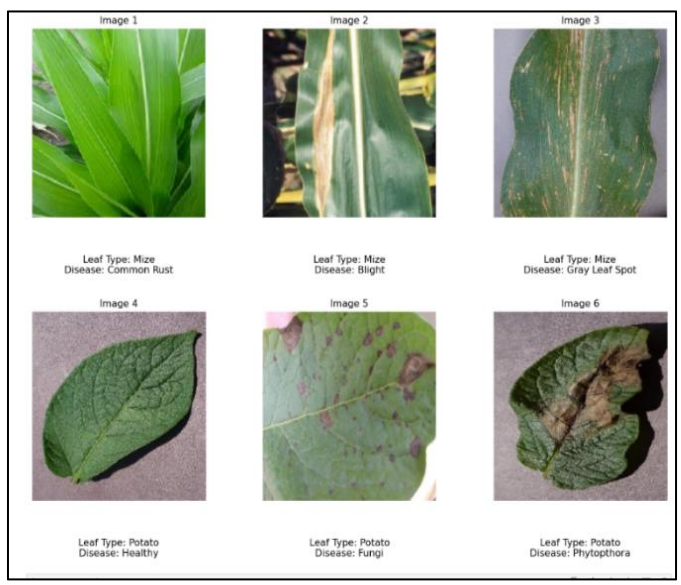

Fig. 7. Final Validation of the Saved Model with Images.

Table 1. comparing with another papers.

Paper	Model	Accuracy	Detected Crops
This paper	ResNet50V2	85.19 %	Maize and Potato
[3]	AlexNet and GoogLeNet CNNs	99.35%	14 crop types
[4]	Deep CNN	96.3%	Apple
[5]	CNN	93%	Cassava
[6]	CNN	97.28%	Tomato
[7]	CNN	91.2%	Date Palm
[8]	CNN	90.16%	Banana
[9]	SVM	97.14%	Pomegranate
[10]	Random Forests	93.2%	Millet
[11]	VGGNet	88%	Cassava
[12]	InceptionV3 with transfer learning	96.6%	Tomato
[13]	ML	95%	Soybean
[14]	ML	90.6%	Wheat
[15]	Deep learning	N/A	Various
[16]	Deep learning survey	N/A	Various
[17]	Machine learning survey	N/A	Various

V. LIMITATIONS

Understanding the limitations of the machine learning demonstration currently being used for leaf disease detection is crucial. The dataset that was used to prepare the demonstration is one of the lock limitations. Although the collection includes a broad range of leaf types and diseases, it could not include every variety and condition that could arise in everyday life. Furthermore, the execution of the model may be impacted by the Caliber and uniformity of the images in the dataset.

A further limitation is the possibility of the demonstration being either overfitted or underfitted during the preparation phase. When a show becomes overly focused on the preparation material, it may overfit, leading to a lackluster generalization based on hidden or underutilized data. Conversely, underfitting may occur when the model is too simplistic and fails to adequately represent the underlying patterns in the data.

In addition, elements like lighting, camera quality, and the time at which the leaf photos are taken may have an impact on how well the model runs. These elements may contain variations in the input data that the demonstration was not designed to properly handle.

VI. DISCUSSIONS

The outcomes of the machine learning demonstration for leaf disease detection show how useful it may be in the early detection and diagnosis of plant diseases. The program can provide useful information to farmers, analysts, and other agricultural experts by accurately identifying the kind of leaf and the associated illness. This information will enable them to design targeted treatment programs and demand appropriate actions.

Nevertheless, it is essential to support, validate, and improve the model's implementation using larger and more diverse information. The model's strength and generalization skills may be improved by combining images from various geological locations, changing environmental factors, and a wider range of plant species and diseases.

VII. CONCLUSIONS

In order to recognize and categorize plant ailments from leaf photographs, a Convolutional Neural Network (CNN) model based on the ResNet50V2 architecture was effectively created for this project. After training on a combined dataset of maize and potato leaves, the model demonstrated an impressive 85.19% accuracy. The results show that the method effectively distinguishes between potato and maize leaves and also identifies the presence and type of diseases affecting them. The model's capacity to extricate the foremost imperative designs and characteristics from the photographs is illustrated by the consistent decrease in preparing and approval misfortunes over the course of 80 ages. The fabulous precision of the demonstrate highlights its versatility and generalization capacities, indeed with the complex dataset comprising photos shot in uncontrolled settings with diverse foundations, areas, and lighting conditions. The achievement of this think about illustrates how profound learning strategies may be connected to unravel down to earth rural issues. This system may incredibly increment the proficiency and exactness of disease diagnostics by computerizing the method of distinguishing and categorizing plant sicknesses. This could encourage incite medicines, lower trim misfortunes, and let agrarian specialists and agriculturists make well-informed choices on how best to oversee illnesses. Aside from that,

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24OCT252

putting such a framework in put may help within the creation of early caution frameworks, which offer defence against any malady episodes and advance more environmentally neighbourly and maintainable cultivating strategies.

REFERENCES

[1]. Barbedo JGA. Plant disease identification from individual lesions and spots using deep learning. . Biosyst Eng 2019; 180: 96–107.
[2]. Ferentinos KP. Deep learning models for plant disease detection and diagnosis. Comput Electron Agric 2018; 145: 311–318.
[3]. Mohanty SP, HDP, & SM. Using deep learning for image-based plant disease detection. Front Plant Sci 2016; 7.
[4]. Sladojevic S, AM, AA, CD, & SD. Deep neural networks based recognition of plant diseases by leaf image classification. Comput Electron Agric 2016; 128: 88–95.
[5]. Ramcharan A, BK, MP, AB, LJ, & HDP. Deep learning for image-based cassava disease detection. Front Plant Sci 2017; 8.
[6]. Selvaraj MG, VA, RH, SN, ES, OW, & BG. AI-powered banana diseases and pest detection. Plant Methods 2019; 15: 1–11.
[7]. Brahimi M, BK, & MA. Deep learning for tomato diseases. Classification and symptoms visualization Applied Artificial Intelligence 2017; 31: 299–315.
[8]. Artzet S, WTS, & RCM. Multimodel approach to resolving banana plant diseases and pest defects using machine learning algorithms. Plant Dis 2019; 103: 2263–2277.
[9]. Kour VP, & AS. Automated detection of diseases in pomegranate plant. Multimed Tools Appl 2020; 79: 16499–16517.
[10]. Coulibaly S, K-FB, DD, & CB. Deep learning for millet head detection and counting in visual images. Comput Electron Agric 2019; 165.
[11]. Too EC, YL, NS, & YL. A comparative study of fine-tuning deep learning models for plant disease identification. Comput Electron Agric 2019; 161: 272–279.
[12]. Polder G, BPM, de VHA, van der WJM, & KJ. Potato virus Y detection in seed potato crops using deep learning on hyperspectral images. Front Plant Sci 2019; 10.
[13]. Nagasubramanian K, JS, SS, SAK, SA, & GB. Plant disease identification using explainable 3D deep learning on hyperspectral images. . Plant Methods 2019; 15.
[14]. Qin J, BTF, RMA, & BWG. Detection of citrus huanglongbing using visible and near-infrared spectroscopy. Comput Electron Agric 2019; 158: 161–174.
[15]. Barbedo JGA. Plant disease identification from individual lesions and spots using deep learning. Biosyst Eng 2018; 180: 96–107.
[16]. Kamilaris A, & P-BFX. Deep learning in agriculture: A survey. Comput Electron Agric 2018; 147: 70–90.
[17]. Singh A, GB, SAK, & SS. Machine learning for high-throughput stress phenotyping in plants. Trends Plant Sci 2018; 23: 810–824.
[18]. Srivastava N, HG, KA, SI, & SR. Dropout: A simple way to prevent neural networks from overfitting. The Journal of Machine Learning Research 2014; 15: 1929–1958.
[19]. King G, & ZL. Logistic regression in rare events data. Political Analysis 2001; 9: 137–163.
[20]. Shawon AJ, TA, & MR. Emotion Detection Using Machine Learning: An Analytical Review. Malaysian Journal of Science and Advanced Technology 2024; 4: 32–43.