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Potato Crop Disease Prediction using Deep Learning

Karthik Kasani
Department of CSE
Vardhaman College of Engineering
Hyderabad, India
karthikkasani4135@gmail.com

Sunanda Yadla
Department of CSE
Vardhaman College of Engineering
Hyderabad, India
sunanda.yadla@gmail.com

Sadhwika Rachamalla
Department of CSE
Vardhaman College of Engineering
Hyderabad, India
sadhwika592@gmail.com

Shanmugasundaram Hariharan
Department of CSE
Vardhaman College of Engineering
Hyderabad, India
shanmugasundaramhariharan@gmail.com

Likhitha Devarajula
Department of CSE
Vardhaman College of Engineering
Hyderabad, India
devarajulalikhitha@gmail.com

Bhanu Prasad Andraju
Department of CSE
Vardhaman College of Engineering
Hyderabad, India
a.bhanuprasad@vardhaman.org

Abstract- **Numerous plant diseases have distinctive visual signs that can be used to recognize and categorize them. Identifying defects in food goods, especially potatoes, requires the use of machine vision and image processing techniques. The claim that potatoes are the most popular vegetable in the world, as made by a rising number of agricultural authorities, are taken into consideration by many countries. Despite the fanfare, potatoes are severely harmed by potato leaf diseases. Many different diseases, including early blight, late blight, and others, will attack potato plants and show their symptoms in the leaves. If these outbreaks are discovered at the beginning stage and timely treatment is considered, the farmer would not be at risk of suffering significant financial losses. The suggested model would effectively identify and diagnose potato leaf stand illnesses using image processing techniques. The Convolutional Neural Network model is utilized in this study to determine the disease from photos of the potato leaf. CNN is used for image classification and performs better than other algorithms in machine learning. These images are then examined using the algorithm provided, and the potato crop leaf is classified as either standard or unhealthy. This promising result led to 96.8% precision, which is highly significant.**

Keywords:***Convolution neural network, potato, late blight and early blight, Image processing***

I. Introduction

A significant food crop that is harvested around the world is the potato. As a origin of carbs, proteins, and vitamins for the consumption of mankind, it is regarded as a crucial crop in both developing and industrialized nations. This plant was first cultivated in Peru and is indigenous to South America [1]. Following wheat, rice, and maize as the most important human food sources is the potato. The physical characteristics of this consumable crop play a significant role in setting the market price at various points throughout the supply chain. Different flaws that can be seen visually have an impact on their quality. The main disadvantages of manual quality control [2], which is still frequently performed by human operators, are subjectivity and cost of labor. As a result, a number of inspection techniques have been created to automate these operations in a more effective and economical manner. The successful employment of computer vision and machine learning techniques to agricultural product quality control [6]. With respect to species, stockpiling, growth period, soil composition, pre-harvest feeding, and the analysis methodologies used, potato tubers' nutritional and chemical composition vary. Potatoes typically include 80–70% water, 16–24% starch, and 4%–5% of other nutrients, such as protein, fat, anthocyanins, minerals, and so forth. Despite having a high carbohydrate content, potatoes also contain large amounts of proteins, minerals, and vitamins [4]. A forecasting algorithm provides an early prediction that could aid in preventing or controlling late blight with the least number of fungicidal sprays possible [1]. Based on 15 years of data, researchers created a disease predicting model and discovered that environmental conditions (temperature and relative humidity) had a substantial impact on disease severity.

The fact that due to various significant potato leaf diseases including early blight, late blight and others, production and export levels have decreased in recent years. The primary pathogens causing late and early blight infections and production losses in many economically significant crops, including potato during vegetative growth, are Phytophthorainfestans and Alternariasolani [7]. The overuse of pesticides has been accompanied by the emergence of resistance to pests and issues with environmental pollution. The use of natural material goods, such as therapeutic plant extracts, can prevent or lessen these issues. The use of image processing to identify illness in plant leaves has been the subject of numerous systematic investigations. Image segmentation, feature extraction, and disease classification are typically the three phases that make up the automatic framework of recognition for plant leaf disease discernment. Image segmentation is a fundamental and important stage for further processing since it affects how well objects can be recognized. Since this study is largely concerned with images, several image samples are needed. Images are taken from kaggle and few from the internet [8]. There are three different categories of processed photographs available. They are healthy, early, and late blight shown in Fig.1. The total amount of images is divided into two groups: one for testing, the other for training. The training component of the images has roughly 80% of them, with the remaining to be in the testing area. The suggested approach would categorize healthy and diseased potato leaves [11]. Farmers can quickly accelerate their growing momentum to prevent diseases from spreading throughout the state.

Table 1: Sample of studied papers

References	Method	Accuracy
[3]	R-CNN	93.22%
[4]	Deep Learning, Transfer Learning	94.94%
[8]	CNN	86.61%
[9]	LS-SVM	90.70%
[10]	SVM and PLS-DA	92.4%
[11]	LS-SVM , BLR, Regression	90.6%

II. RELATED WORK

Researchers employed machine learning, SVM, ANN, techniques like autoencoders, localisation to investigate agricultural diseases predicting. Sofial et al. [3] showed on the chosen images, an autoencoder and SVM combination were used to find destroyed and greening faults in a patch-by-patch fashion. The potato was categorized in accordance with the severity of the blemish using the localization results. In a test dataset, study was able to achieve a precision of 92% and a recall of 91% for the final potato-wise classification. Khalid et al. [5] took five algorithms used in this study are AlexNet, VggNet, LeNet, ResNet,, and the recommended model. To distinguish between the normal and abnormal characteristics of potato leaves, normal and disorder-influenced leaf was used for the presented model. These images are then examined using the algorithm offered, and the potato plant leaf is classified as either normal or unhealthy. This model's 97% high precision was established. Deep learning has been used in a research as far potato disease infection is concerned and led to promising results [13-16]. Kaitlin M. Gold et al. [19] with 89–95% accuracy, each pathogen's individual disease development phases could be distinguished from corresponding controls. Notably, study achieved higher than 75% accuracy in separating latent P. Infestans infection from both dormant and indicative solani infection. The experimental results taking into account the hierarchical structure of spectral-spatial information, greatly improves accuracy, with average accuracies of 96.08% for the testing dataset and 95.75% for the independent dataset [12].

Figure1:Diseased potato

To assess the performance for identifying potato illness, four classifiers based on the k-NN, SVM, ANN, and RF approaches were used. According to the findings [17], SVM had the maximum accuracy at 92.1%. Many researchers have used numerous patterns to transform the actual image taken in RGB form into an image in CIELAB color space. The researchers also developed features at the feature level. The researchers provided segmented photos that were classified using random forest algorithms. Fruit illness was discovered after recognition, and this method was applied.

III. MODEL BUILDING

CNNs are composed of multiple layers, including: Convolutional layers, Pooling layers, Fully connected layers and more. The CNN algorithm is utilized to create the sequential model. Convolution two-dimensional layer for manipulate images & image input size which is(256,256) for any size image given as input. Keras aids in the section-by-section development of this model. Additionally, it is possible for the CNN model shown in Fig.3 to modify two more parameters, such as the quantity of convolutional layers and the size of the part. Convolutional layer count is important. The collection of more features will be aided by the addition of more layers. A model and distinction are better evaluated and made when there are more features. However, adding much more layers than necessary is unnecessary because doing so will cause the data to be overfit, which will make the model more complex. Thus, beyond a certain point, adding additional layers leads the data to skew. The tables show these bounds, which are referred to as hyperparameters. To make sure no layer activation outputs are erupted or detonated at that time, weight initialization is used.

All leaf data contain some noise because of the close measurement distance; therefore, a low-pass filtering operation, such as Gaussian filtering, is essential for reconstructing an image in which the noise is balanced by surrounding pixels [13]. The segmentation outcomes of the leaf data can be harmed by Gaussian filtering, which can also blur the structure and design of the leaves [21,21,22].

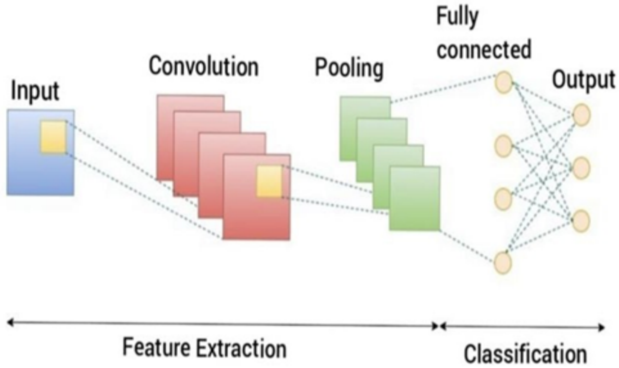

Figure 2: CNN Architecture

A guided filter is used to reduce noise in a picture while maintaining the leaf's edge characteristics and texture information, with the filtering output being a local linear shift of the guiding image. A flat layer that served as a bridge existed for both the dense layer and the two-dimensional layer of convolution. SoftMax was proposed as anactivation for foretelling basedonmaximal possibilities inthe framework. Below is the equation for the SoftMax function:

$$P(x) = \frac{eX^T W^l}{\sum_{k=1}^{k} eX^T W^l} \quad (1)$$

IV. METHODOLOGY

4.1 Proposed System Diagram:

For the purpose of augmenting the dataset, the photos are first obtained and then created. The dataset that the CNN model was built on after being enhanced is trained and tested on the model. The model eventually recognizes,displays the outcome after performing the train and test. The model block diagram is displayed below Fig.3:

4.2 Datasets:

Data is the main part of project which requires lot of images because the work requires several training followed by testing of images. Therefore, when gathering photographs, we must be conscious of a number of critical factors, including image sizes, resolutions, and quality, as well as the potato leaf disease condition. The initial step is to get the image data from Kaggle, Internet, Web Scrapping tools and as many manually captured photographs as feasible [12]. However, not all of the merged images are really useful to the project. Some photographs' resolutions are shallow that it's difficult to tell which ones are damaged and which ones aren't. This is why few photos each for early blight, healthy, and late blight are assigned for the training goal. In this research, sample of potato leaf images from Kaggle dataset is chosen for study. This dataset contains 2150 images of potato leaf. It has 3 class of sample of Healthy Leaf, Early Blight and Late Blight. The total amount of images is divided into two groups: one for testing, the other for training. The training component of the images has roughly 80% of them, with the remaining to be in the testing area. The accuracy of model is achieved 96.8%. Classifier is helpful in early and accurate prediction of the leaf diseases of potato crop.

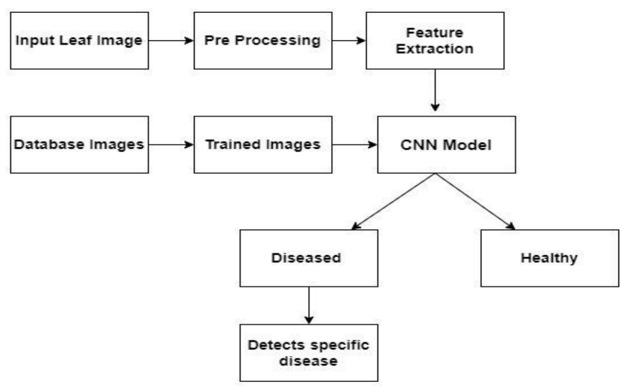

Figure3:Block Diagram

4.3 Algorithm Selection:

Deep learning models called convolutional neural networks (CNNs) are extremely effective at classifying images. They take their cues from the brain's visual system and can immediately pick up on hierarchical representations of images. A dataset of photos of both healthy and diseased potatoes would be required to train a CNN for potato disease prediction. The associated disease or class needs to be labeled on these images. Then, using this dataset as training data, the CNN would be trained, using a technique called backpropagation to tweak the network's weights and reduce classification error [15]. Once trained, the CNN may be used to categorize new potato photos as healthy or diseased. To do this, pictures of potatoes in the field might be taken, and a trained CNN could be used to determine whether a disease is present.The lack of labeled information is one of the major obstacles to utilizing CNNs to forecast potato disease. It is important to take pictures of both healthy and diseased potatoes in various lighting, angle, rotation, and zoom conditions. Researchers have artificially increased the dataset's image count using data augmentation techniques to get around this problem. Convolutional neural networks (CNN) treat documents using two- dimensional convolution procedures.

$$O=\frac{(W-F+2P)}{(S+1)} \quad (2)$$

4.4Training and Testing:

This dataset is split into two portions, each receiving 80% of the image dataset for training and the rest 20for testing and validation dataset. To train the computer to understand the requirements, partial data must first be prepared, cleaned, and labeled before being sent to training. Any entries that are false, incomplete, confusing, or deceptive should be removed [18]. Without high-quality data, machine learning is ineffective. Patterns can be discovered through data analysis, and as a result, the trained algorithm is ready to take new data and predict. It is primarily been trained on a training data set. The unused data, also known as the test set, is utilized to test the software. The threshold receives these test results.

V. PERRFORMANCE EVALUATION

5.1 Learning Rate:

The learning rate is a hyperparameter that regulates how frequently the optimizer updates the model's parameters while it is being trained. It is used to regulate how quickly the model picks up new information from the training data in several optimization algorithms, including stochastic gradient descent and others. The model will converge more slowly with a lower learning rate, but its parameters will be less likely to overshoot their ideal ranges [17]. The model will converge more quickly with a higher learning rate, but the parameters may exceed the ideal values and arrive at a less-than-ideal outcome. Accuracy, precision, recall, and the F1 measure are the four performance measures used to assess the CNN model. The effectiveness of the suggested model is evaluated using the F1-score.The F-score serves as a recall and precision indicator. The F1-score is the value that receives a weighted beta worth accuracy when calculating the F-score. The accuracy measure is used to express the proportion of correct predictions. These formulas are used to determine the F1-score and Accuracy [2].

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

$$\text{F1-score}=\frac{2\times precision \times recall}{precision+recall} \quad (4)$$

F1-score is a mean between precision and recall where as precision is positive predictive value and recall is True positive rate or sensitivity. A confusion matrix's basic structure for our model is as follows: False Positives (FP) vs. True Positives (TP), True Negatives (TN) vs. False Negatives (FN), where TP denotes the total number of correctly predicted positive outcomes, FP denotes the total number of false positives, FN denotes the total number of false negatives, and TN denotes the total number of true negatives. The function "fit ()" is used to train the model. Validation data testing on the dataset. The fit function, which rhythmically runs the algorithm over the data, sets the number of epochs.

After the training phase is finished, the testing method is configured. It approves of the trained CNN model's potential [14]. The stochastic gradient descent variant known as the Adam optimization technique has lately gained more popularity for deep learning applications in computer vision and natural language processing. This is a useful optimization tool to adjust the learning rate during the training period. Categorical cross- entropy is used to train the system and includes a "accuracy" metric to reflect the accuracy score on the validation set. This makes it easy to realize our loss function.

5.2 Result and Outcome:

The Jupyter notebook is implemented to carry out the whole workflow. Various diseased potato leaf images were produced in the first stage in order to classify. The images are selected from a folder. The outcome of the prediction is shown after the images have been taken. For Early blight it is noticed to see a circle that overlaps the spots that is yellowish or bright green-yellow. Large spots can occasionally cause the entire leaf to turn yellow and die. Late blight demonstrates how it has impacted the foliage. Leaf flecks start off as little, sporadic dots that range in color from light to dark green. At cool, damp weather, the fleck quickly expands into sizable brown to purple-black regions.The disease can kill the plant by destroying entire leaflets or spreading into the stem from the petioles and following is our prediction shown in Fig.4.

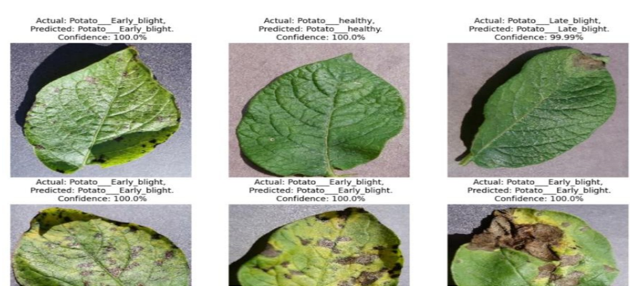

Fig.4: Output visuals of leaf classification

Table 2: Comparison of results of existing work and proposed work

Algorithm	Accuracy (%)
SVM+ PLS-DA	92%
LS-SVM	90.70%
R-CNN	93.0%
CropdocNet	95.75%
Proposed Work	96.8%

VI. CONCLUSION

In this study, we investigate the use of convolution neural networks and image processing to identify and categorize potato diseases. Three classes' namely healthy, early blight and late blight were classified as a sizable database with numerous variants. In addition to being used as a filter to identify pixels that needed further examination, a Convolutional neural network was trained to categorize photos of potato leaves. The study results achieved a decent outcome by employing our strategy. The accuracy of the CNN-based method is greater than that of other methods. The convolution layer brings out the distinctive features of the image, and the convolution layer is issued with a pooling layer to reduce the majority of the feature data. Most potato diseases are correctly classified, as shown by the confusion matrix. This study's findings and model's detection accuracy of 96.8%showthatCNN performed better than other research methods. In order to make it simple to use and understand for the farmers, we intend to create an Android application in the future.

REFERENCES

[1] D.Shtienberg, "Applications of epidemiology in the management of Ascochyta blight in chickpea and lentil", In: Compendium of Chickpea and Lentil Diseases and Pests. APS Press, St Paul, Minnesota, USA. pp 22, 2020.

[2] R. Reddy, S. Rachamalla, S. M.S. Yoosuf and G.R. Anil, "Convolutional Neural Network Based Intrusion Detection System and Predicting the DDoS Attack", In: Jacob, I.J., Kolandapalayam Shanmugam,S.,Izonin,I.(eds) Data Intelligence and Cognitive Informatics Algorithms for Intelligent Systems, Springer, 2023.

[3] Lee, HS., Shin, BS, "Potato Detection and Segmentation Based on Mask R-CNN", Journal of Biosyst. Eng, vol. 45, pp. 233–238, 202).

[4] Dasgupta, S.R., Rakshit, S., Mondal, D., & Kole, D.K., "Detection of Diseases in Potato Leaves Using Transfer Learning", *Computational Intelligence in Pattern Recognitio, 2019.*

[5] A. Khorramifar, R. Mansour, H. Karami, U. M. Toboła, and M. Gancarz, "A Machine Learning Method for Classification and Identification of Potato Cultivars Based on the Reaction of MOS Type Sensor-Array", Sensors,vol. 21, no. 17: 5836, 2021.

[6] M. K. R. Asif, M. A. Rahman and M. H. Hena, "CNN based Disease Detection Approach on Potato Leaves," 2020 3rd International Conference on Intelligent Sustainable Systems (ICISS), Thoothukudi, India, 2020, pp. 428-432, doi: 10.1109/ICISS49785.2020.9316021.

[7] Henshall, W. R., Dani Shtienberg and Robert M. Beresford. "A new potato late blight disease prediction model and its comparison with two previous models." New Zealand Plant Protection 59 (2006): 150-154.

[8] N.K. Qinghua Su, D.F.A. Al Riza and H. Habaragamuwa, "Potato quality grading based on depth imaging and convolutional neural network", vol. 2020.

[9] [9] Q.Z. Wenwen Zhang , M. Huang, Y. Guo and J. Qin , "Detection and classification of potato defects using multispectral imaging system based on single shot method, Journal of Food Analytic Methods,Springerp.2920–2929, 2020.

[10] K.M Ruben Van De Vijver, K. Heungens, B. Somers, D. Nuyttens, I. Borra-Serrano, P. Lootens, I. Roldán-Ruiz, J. Vangeyte and W. Saeys, " In-field detection of Alternaria solani in potato crops using hyperspectral imaging", Computers and Electronics in Agriculture, vol. 168, 2020.

[11] Yingwang Gao JGY (2016) CCD-Based Skinning Injury Recognition on Potato Tubers (Solanum tuberosum L.): A Comparison between Visible and Biospeckle Imaging. J Sensors.

[12] Shi, Yue & Han, Liangxiu & Kleerekoper, Anthony & Chang, Sheng & Hu, Tongle. (2022). Novel CropdocNet Model for Automated Potato Late Blight Disease Detection from Unmanned Aerial Vehicle-Based Hyperspectral Imagery. Remote Sensing. 14. 396. 10.3390/rs14020396.

[13] Shtienberg, D. & Doster, M.A. & Pelletier, J.R. & Fry, William. (1989). Use of Simulation Models to Develop a Low-Risk Strategy to Suppress Early and Late Blight in Potato Foliage. Phytopathology. 79. 590- 595. 10.1094/Phyto-79-590.

[14] Arshaghi, Ali & Ashourian, Mohsen & Ghabeli, Leila. (2022). Potato diseases detection and classification using deep learning methods. Multimedia Tools and Applications. 10.1007/s11042-022-13390-1.

[15] MacKenzie, D. R. "Association of potato early blight, nitrogen fertilizer rate, and potato yield." Plant Disease 65, no. 7 (1981): 575-577.

[16] Ahmad, Nadeem & Khan, Muhammad & Khan, Nasir & Ali, Mubasher. (2015). Prediction of Potato Late Blight Disease Based upon Environmental Factors in Faisalabad, Pakistan. Journal of Plant Pathology & Microbiology. 1. 1-6. 10.4172/2157-7471.S3-008.

[17] H. Chaojun, Z. Jiajun, Y. Tang, H. Yong, M. Aimin, H. Huasheng and L. Shaoming, "Recognition of early blight and late blight diseases on potato leaves based on graph cut segmentation", Journal of Agriculture and Food Research, vol. 100154, 2021..

[18] Gold, Kaitlin M., Philip A. Townsend, Adam Chlus, Ittai Herrmann, John J. Couture, Eric R. Larson, and Amanda J. Gevens, "Hyperspectral Measurements Enable Pre-Symptomatic Detection and Differentiation of Contrasting Physiological Effects of Late Blight and Early Blight in Potato", Remote Sensing, vol.12, no. 2: 286, 2020.

[19] O. Dor, G. Shani, O. Erlich and L. L. Tsror. "Using Deep Learning for Image-Based Potato Tuber Disease Detection." Phytopathology 109 6 (2019): 1083-1087.

[20] G. LakshmiPriya, G. and S. Hariharan, "A study on predicting patterns over the protein sequence datasets using association rule mining", Journal of Engg Science and Technology, vol.7, issue.5, pp.563-573, 2012.

[21] G. L. Priya and S. Hariharan, "A comparative study on existing methodologies to predict dominating patterns amongst biological sequences", In 2011 Third International Conference on Advanced Computing, pp. 210-215, 2011.

[22] Bhalla, K., Koundal, D., Sharma, B., Hu, Y. C., & Zaguia, A., "A fuzzy convolutional neural network for enhancing multi-focus image fusion", Journal of Visual Communication and Image Representation, vol. 84, 103485, 2022.