

TOWARDS IMPROVED CLASSIFICATION OF POTATO TUBER DISEASE BASED ON HYBRIDISATION OF ResNet ARCHITECTURE AND NAIVE BAYES CLASSIFIER

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ABSTRACT: Crop diseases are a major challenge in agriculture as they affect farm produce and often lead to reduced yields thereby threatening food security. Several studies have proposed different Machine Learning (ML)-based approaches for the classification of diseases in crops. In this paper, the focus is on building two-stage Potato tuber disease classification model using Residual Network (ResNet-18) architecture and Naive Bayes (NB) algorithm. The image crop dataset was collected from Mendeley repository. The Potato disease classification model was built by using Resnet-18 architecture at feature extraction layer while Gaussian Naive Bayes was used for the potato image classification task. The crop classification model was trained and tested on the chosen dataset of potato crop images using training and test ratio of 0.80 and 0.20 respectively. Experimental results showed that the use of the ResNet-18 model helped the NB-based potato disease classification model to achieve high accuracy in classifying both healthy and diseased crops. The model achieved 94.45%. The study demonstrated how the hybridization of a deep learning approach for feature selection and a classical learning algorithm called Naive Bayes for the potato crop disease classification. Thus, the proposed model can be effective for potato disease classification there reduce losses, and improve agricultural productivity.

KEYWORDS: Classification Accuracy, Crop Diseases, Image Classification, ResNet Architecture, Food Security

I. INTRODUCTION

Globally, the agricultural sector plays a crucial role in ensuring food security and sustaining livelihoods (Smutka et al., 2009). However, food crops are increasingly threatened by various diseases that can lead to significant yield losses and economic hardship for farmers. Sadly, agricultural sector globally is faced with several difficulties and one of such challenges is crop diseases. Early detection of these diseases is essential for effective management and mitigation strategies. Recent advancements in technology have created uncommon opportunities for farmers to monitor their crops and identify potential threats in real-time or to have systems that can identify diseases in crops in the future based on historical data. It has been argued that to minimize the harm that crops diseases cause to food security, farmer earnings, and companies in general, early diagnosis of crop diseases is crucial (Adegbola et al., 2024). A crop disease is anything that prevents the crop from performing to its maximum potential. The use of Artificial Intelligence in agriculture is very promising as it enables us to have transformation to agricultural practices and thereby guarantee productivity (Pande & Moshra, 2024). Detecting crop diseases early is critical for efficient crop yield and preventing economic losses in the agriculture industry. Machine learning approaches are widely used in agriculture for detecting and recognizing weeds, fruit grading, and identifying disease infestations of crops (Riley et al., 2002; Ma et al., 2018). Zhang and Wang (2020) have emphasized the reason while mobile technology can also be integrated to farming so as to aid the farmers more. Potatoes are chosen as the food crops in this study. Potatoes are widely cultivated and consumed due to their high nutritional value and adaptability to diverse climatic conditions. Generally, Potatoes are highly susceptible to a variety of diseases such as early blight, late blight, soft rot, and black spot bruising, which can lead to significant yield losses if not detected and managed early. The decision to focus on potato was informed by its agricultural importance, the economic impact of its diseases on smallholders, commercial farmers alike, as well as the pressing need for robust, automated

solutions to support early disease diagnosis and management in potato farming systems. In potatoes, some studies focus on using leaf images for disease identification while some use tuber images as the basis. Gopal and Velswamy (2025) have pointed out that computer vision is very important in precision agriculture by making the automated disease diagnosis and decision-making through real-time data possible. This study-built ML-based potato disease classification model by combining ResNet Architecture and Naive Bayes classifier at different layers. The investigation is targeted at determining the strengths of combining the two approaches for achieving improved classification of potato tuber disease in the chosen image dataset.

II. RELATED WORKS

Chen and Liu (2025) proposed a method for Potato Leaf Disease Classification. The researchers pointed out that the approach they used produced promising classification results when compared to similar studies. Similarly, Gopal et al., (2025) built learning models for the classification of potato leaf disease. The study focused on the diseases that ravaged potato leaves. The authors argued their methods built performed excellently in the identification of the disease. Singla et al. (2024) conducted a thorough examination of various ML techniques in crop diseases classification. The study emphasized the various methodologies, datasets, performance metrics, and practical applications used in the studies. Furthermore, the review offered a critical evaluation of current models, highlighting their limitations and identifying existing gaps. The authors concluded that although ML-based approaches show significant promise for improving agricultural disease management. Nikith et al. (2023) developed an approach for detecting guava leaf diseases using SVM. This was accomplished by utilizing a dataset of 70 images, which underwent pre-processing and segmentation employing K-means clustering. Feature extraction was conducted using a gray-level co-occurrence matrix, which captures the frequency of different combinations of intensity levels occurring together in an image. Subsequently, these extracted features were employed to train an SVM classifier, achieving an accuracy of 98.17%.

Mewada et al. (2021) also built a system for leaf extraction and disease classification employing SVM. Leaf image acquisition was conducted using a Raspberry Pi, which also facilitated image transmission over the internet via an online web-based server. The images were delivered on a host PC where the image features were extracted after being segmented using the watershed and graph cut segmentation model. SVM was employed for classification, achieving an impressive accuracy rate of 97%. Yousuf and Khan (2021) built a hybrid model that is made up of Random Forest (RF) and KNN was developed to identify plant diseases. The methodology comprised of four fundamental stages: initial pre-processing, segmentation through K-means clustering, extraction of texture features utilizing the gray-level co-occurrence matrix (GLCM) algorithm, and ultimately, classification achieved through the ensemble model formed by integrating the two classification techniques, RF and KNN. RF techniques were applied for optimum feature selection, while KNN was used for classification. The performance of this ensemble model was evaluated, and it was seen to have achieved 97.8%. Abbas et al. (2021) proposed a hybrid deep learning model integrating CNNs with Long Short-Term Memory (LSTM) networks to capture both spatial and sequential features of plant leaf images. Their approach outperformed conventional CNN models in classification performance. For real-time disease detection, the You Only Look Once (YOLO) object detection framework has been widely adopted due to its efficiency. Zhang et al. (2020) built a mobile-based system that integrates machine learning algorithms for real-time crop disease detection. The authors combined CNNs and SVMs in a hybrid model, achieving impressive accuracy and processing speed. Oppenheim et al. (2019) built a deep learning model for the detection of potato tuber disease using image dataset. The chosen DL algorithm in the study is CNN. The authors claimed that their approach achieved very good result in classification accuracy as one of the pioneer works in this direction.

III. METHODOLOGY

This study used a combination of ResNet and Gaussian Naive Bayes for the building of intelligent model that can classify potato disease in image dataset better. The general workflow of the various stages followed in the Potato Tuber disease classification is as shown in Figure 1.

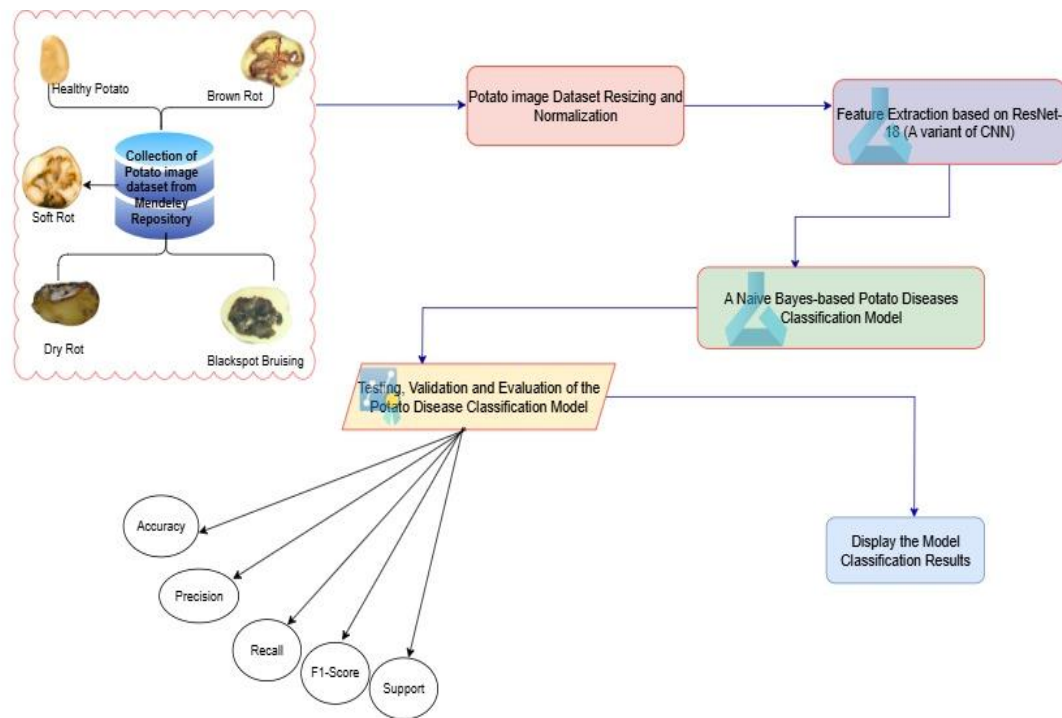


Figure. 1: Methodological Flow of the Potato Tuber Disease Classification Model

As part of the steps used in the methodology of this study, the Potato tuber disease image dataset was pre-processed through resizing and normalization. Based on the information made available by the authors of the dataset, the dataset is already augmented. The importance of the image pre-processing stage is to ensure that the image dataset is available in usable format. For the purpose of extracting the most promising features from the image dataset collected. This study used pre-trained CNN named Resnet-18 for the feature extraction process. To be able to use the ResNet as feature extractor, the final layers of a pre-trained CNN were removed, and the output of a preceding convolutional layer was used as the feature representation. Thereafter, the images were preprocessed (resized, normalized) to match the input requirements of the pre-trained model. The preprocessed images were passed through the variant of CNN so as to obtain the feature maps or flattened feature vectors in a process named the Forward Pass. The extracted features by the ResNet-CNN are then used as input features in the Naive Bayes Classifier for the potato disease image classification task. A train_ratio of 0.80 and test_ratio of 0.20 were used while building the model. This entire process is repeated for a specified number of epochs. The number of epochs is an important hyperparameter that affects how the training process of the potato disease classification model and the model's performance goes. Seven epochs were used in the experimentations. The performance of the model at each epoch was monitored and the best performance across the metrics was recorded.

Dataset Collection and its Description

The dataset used in this study is an image dataset that contains five different potato classes, namely: Healthy Potato, Blackspot Bruising Disease, Soft Rot Disease, Brown Rot Disease, and Dry Rot Disease. The dataset was released by Mafi et al. (2023). The authors of the dataset have already pre-processed it as mentioned earlier. The dataset contains the original dataset and the augmented one as a whole. This study made use of the augmented dataset so that we can have dataset that is sizable enough and achieve a model that can generalize well. This study made use of the augmented version of the dataset.

The Feature Extraction Algorithm

Residual Network (ResNet) is a type of Convolutional Neural Network (CNN) that uses residual connections to solve the gradient problem in deep networks. The architecture was proposed by He et al. (2016). ResNet-18 as an 18-layer deep CNN architecture was designed for image classification problems. It has been argued that Resnet-18 is a highly effective deep learning architecture known for its ability to learn complex, hierarchical features from data, particularly image. The ResNet-18 is used for extraction the most useful features in the potato image dataset. The algorithm works by using the strategy of fitting the residual mapping rather than have layers learn the underlying mapping. Therefore, this approach will make the network to fit instead of using the initial mapping of $H(x)$, where $F(x) := H(x) - x$ which gives $H(x) := F(x) + x$.

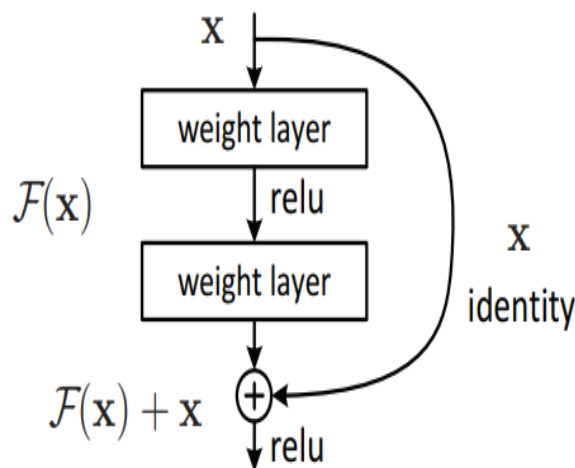


Figure 2: Residual learning: a building block (He et al., 2016)

The Classification Algorithm

Naive Bayes is the chosen as the classification algorithm in this paper. The algorithm is a probabilistic classifier that works on the assumption that every feature is independent (Mitchell, 20218). This assumption allows the classifier to avoid the curse of dimensionality. In this study, it classifies potato disease dataset by computing the posterior probability of each class given the features of food crop.

$$P(C|X) = \{P(X|C) P(C)\} / P(X) \tag{1}$$

$P(C)$ is the probability of each face occurring in the dataset.

$P(X|C)$ is the likelihood of observing a feature vector X knowing that it belongs to a class C . Naive Bayes assumes feature independence, it is computed as the repeated product of each observed feature.

$$P(X|C) = P(X_1|C) * P(X_2|C) * P(X_3|C) * \dots * P(X_n|C) \tag{2}$$

$P(X)$ is the probability of observing the feature vector X across all classes. It is used as a normalization constant; it is the same for every class when classifying a new instance. $P(X)$ can be omitted when classifying since it does not affect the posterior probability.

Metrics for the Model Evaluation

The following metrics were used to evaluate the performance of the developed model:

- (a). **Accuracy:** The accuracy of the models is measured by the correctness of the models in recognizing the right potato as good or bad.

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

(b). Precision: The precision is a measure of how correct the model is in identifying a correct face belonging to a particular person.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (4)$$

(c). Recall: Recall is the measure of the correct number of faces the model has predicted successfully.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (5)$$

(d). F1- Score: This is the harmonic mean between precision and recall. It helps to provide a balanced measure between precision and recall.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (6)$$

(e). Training and Evaluation time. This metric is measured in seconds. The time spent for training and testing the model are evaluated. The time library in Python was used to perform this evaluation.

IV. RESULTS AND DISCUSSION

Based on the exploratory analysis carried out, there are 495 original images of potatoes. Then, in order to increase the number of data points, shifting, flipping, zooming, shearing, brightness enhancement, and rotation techniques were used by the dataset authors to create a total of 3,465 augmented images from these original images. The augmented images were used in the study with a view to achieving efficient **ResNet+NB** Potato tuber disease classification model. Some of the results of the exploratory data analysis carried out on the image dataset are as shown in tables 1 and 2 as well as figures 3 to 8.

Table 1: Summary of the Dataset based on the EDA carried out

Description	Number
Total Classes:	5
Total Images:	3465
Avg Images/Class:	693.00
Min Images in a Class:	105
Max Images in a Class:	1295
Most Common Image Size:	(512, 512) (3465 times)
RGB Images:	3465
Grayscale Images:	0
Corrupt Images:	0

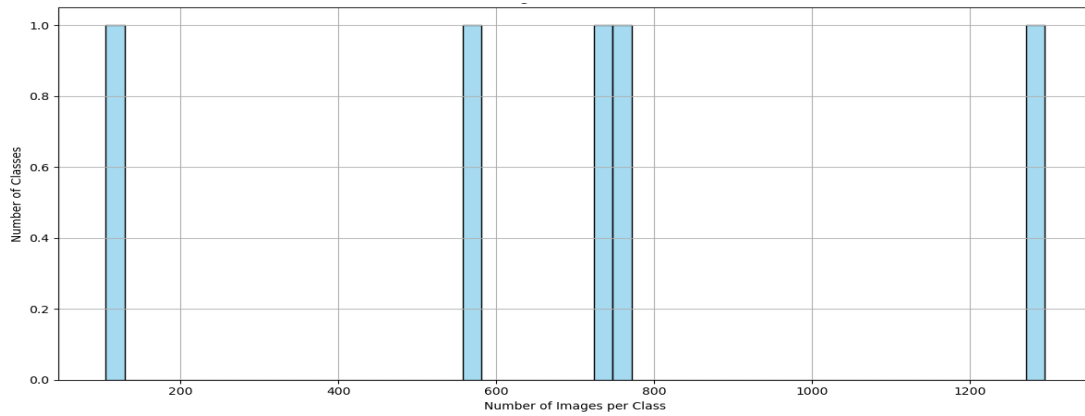


Figure 3: Histogram of Class Sizes in the Dataset

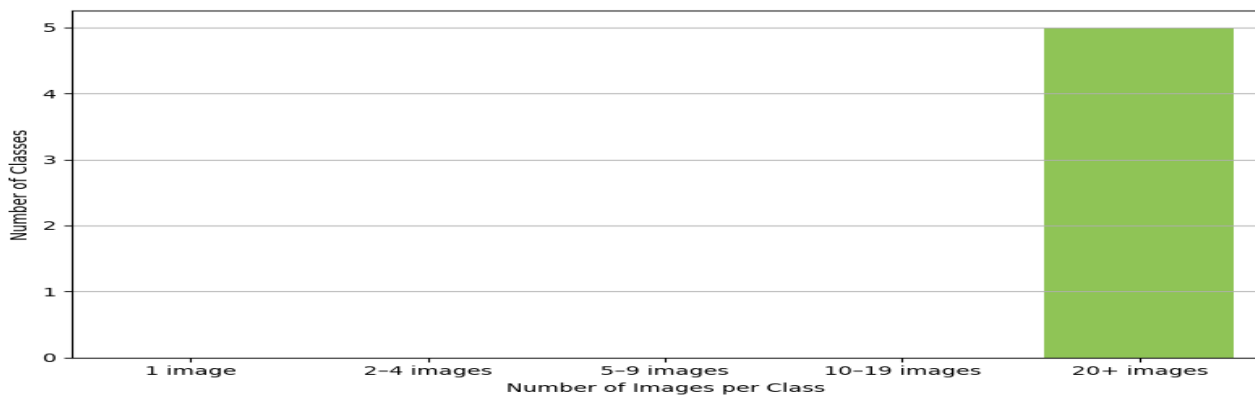


Figure 4: Class Count Distribution in the Dataset

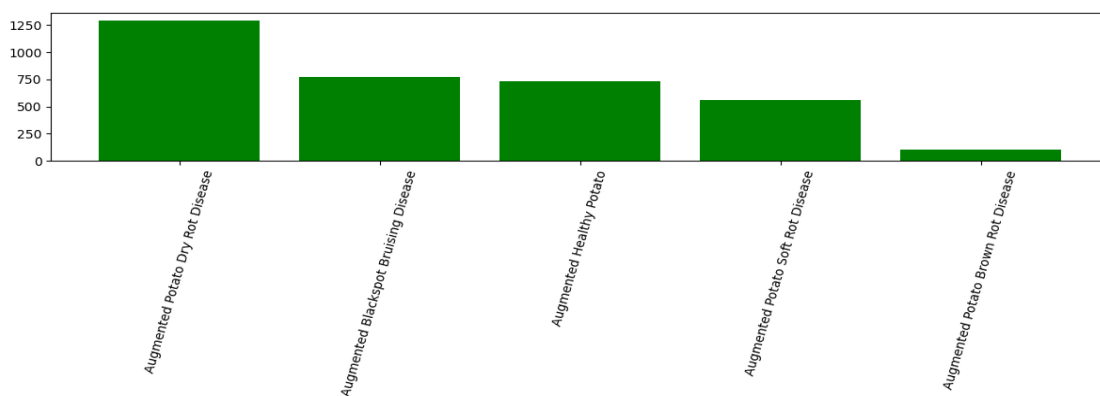


Figure 5: The Top 20 Classes by Image Count in the Dataset

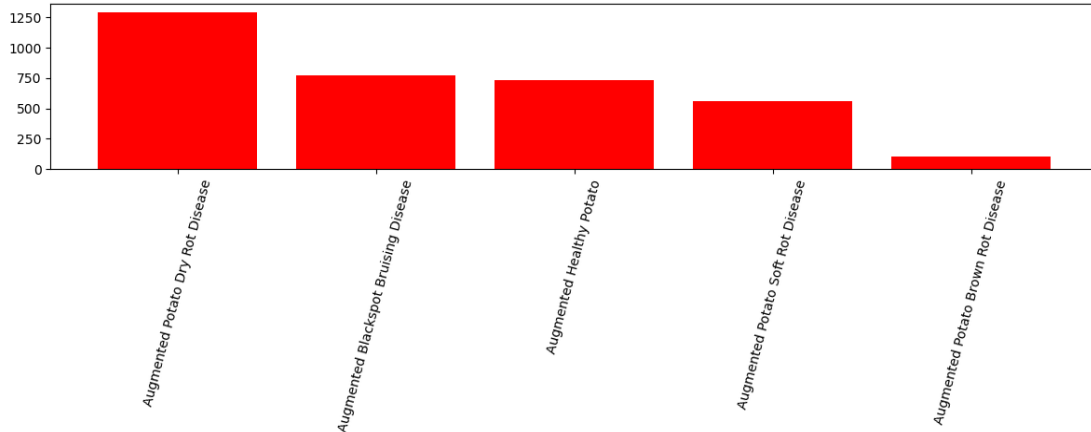


Figure 6: The Bottom Classes by Image Count



Figure 7: Random Samples of Healthy and Unhealthy Potato from the Dataset

Table 2: Description of the Potato Image Dataset based on Splitting

Item	Number of Items
No of Classes:	5
Real images split:	2772 train (80.0%), 693 test (20.0%)
Total test samples (original only):	693

Table 2 shows the results of the 80:20 training test split ratios used on the dataset that is applied in the study.

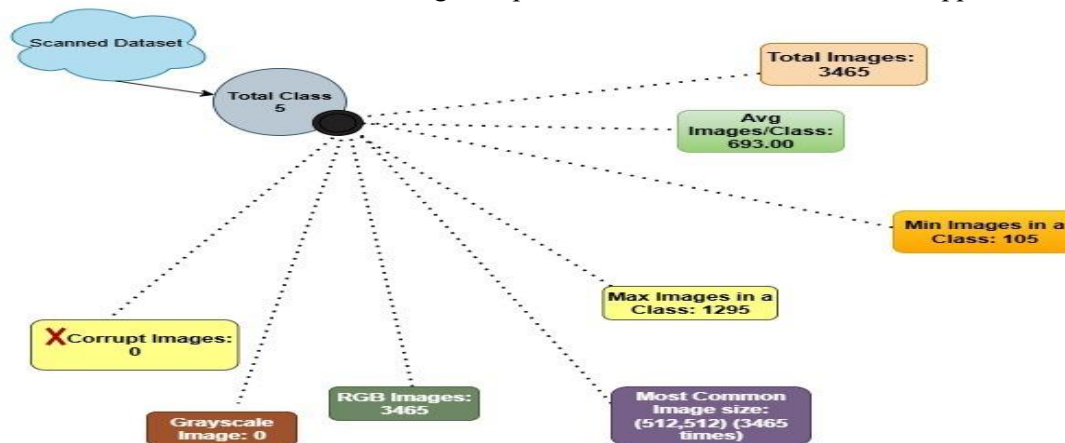


Figure 8: Statistical Report of the Classes in the Image Dataset

Results of the Model Performance

Table 3: The Time Taken in each Epoch

Epoch	Loss	Time Taken (in second)
1	6.4482	168.8
2	5.8146	100.3
3	5.5707	108.6
4	5.3574	102.2
5	5.1887	94.0
6	5.0828	74.7
7	5.0061	73.8

Table 4: Results of the Potato Disease Classification Model

Model/Metric	Accuracy (%)	Precision	F1-score	Recall	Evaluation Time (s)
Resnet-18+NB Classifier	94.45	0.9391	0.9412	0.9412	0.02

Comparing our study with Potato Tuber Disease Classification by Oppenheim et al. (2019)

Oppenheim et al. (2019) carried out an overall accuracy of their CNN-based Potato Tuber Classification model with respect to the amount of training data. It was reported that their best trained model which was trained on 90% of the dataset and tested on the remaining 10%) correctly classified 96% of the images as more data increases performance. The study emphasized only accuracy as against other metrics being considered in our own approach. Our approach can also be seen to be an improvement when compared with some recent and similar studies that focus on potato tuber-disease classification.

Discussion of Results

This study first of all carried out detailed exploratory analysis of the dataset with a view to providing further insights on the basic characteristics of the dataset which informed what kind of pre-processing methods to be used in the study. The study then applied the combination of ResNet architecture and Naive Bayes Classifier to achieve improved classification of potato disease in the chosen potato image dataset. The thorough analysis of the dataset that was carried provided information about the patterns in the dataset better. The results of the EDA are as shown in figures 3 to 8 as well as Tables 1 and 2. Similarly, the insights provided by the EDA guided the pre-processing of the dataset using image resizing and normalization. Th study further confirmed that the data pre-processing procedure is a crucial step in every classification-based machine learning problem. The dataset was pre-processed so that the image dataset can be found useful for the model building, in line with the general practice in ML-based modeling. The extracted features from the dataset were then fed in the chosen classification algorithm which produced the potato disease classification results presented in table. Experimental results showed that the model is very efficient in time of all the metrics used for the performance evaluation. For instance, the model achieved an accuracy of 94.45%, precision of 0.9391, recall of 0.9412, and f1-score of 0.9412 and evaluation time of 0.02seconds. Apart from this, it was deduced that the evaluation time of the model is 0.02seconds. Thus, it can be argued that the approach used in this study achieved as promising results in all the chosen metrics. At the evaluation time, the time used is lower than that of the training time. It was equally obtained that the scores recorded for accuracy, precision, f1-score, recall are very

promising. The findings in this study showed that the hybridized model has significant practical implications in potato tuber disease classification.

V. CONCLUSION

This study built a hybridized learning model that is based on ResNet-18 architecture and Naive Bayes classifier. The study emphasized the use of a popular deep learning method named ResNet architecture for the extraction of useful features from the image-based potato dataset collected. Then, emphasis was shifted to the combination of the ResNet algorithm and Naive Bayes classifier for a better classification result from the collected potato image dataset. The dataset is a benchmark dataset that is used to classify the diseases in the Potato tuber crops. In this study, experimental results showed that the model that is built from the combination of ResNet-18 and Gaussian Naive Bayes achieved exceptional performances in accuracy, precision, recall and f1-score. The evaluation time is also very small compared to what is found in most recent and relevant studies. In summary, the results indicated that the model is very efficient in time of all the metrics used for the performance evaluation. These results emphasized the strong potential of a combination of deep learning method and traditional learning algorithm for a robust potato tuber disease classification in real-life smart farming environment.

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