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Real-time disease recognition in Irish potato using Deep Learning on Jetson Nano

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Abstract

Potato early and late blights are major threats to long-term potato production, affecting many farmers worldwide, notably in Africa. In order to ensure sufficient supply and food security for the world's rapidly expanding population, early identification and treatment of the potato blight diseases are essential. As a result, using computer vision for potato disease diagnostic systems may be able to overcome the limitations of the traditional leaf disease diagnosis process, which is time-consuming, inaccurate and expensive. Computer-assisted diagnosis of potato leaf disease is becoming more widespread. However, there are several limitations to the use of computer vision for real-time potato disease recognition, such as strong image backgrounds, vague symptom edges, lack of real-field potato leaf image data, variation in symptoms from the same infection, and a lack of an efficient real-time system. To address the aforementioned issues, the current study examined a cutting-edge convolutional neural network (CNN) called DenseNet121 running on the NVIDIA Jetson Nano for real-time classification of potato leaf diseases. Transfer learning with publicly available online potato leaf datasets improves the resilience of the model. The deep-learning-based approach described was found to be effective in the automatic identification of potato blight diseases. By precisely identifying the plants affected by potato blights, site-specific fungicide treatment has the potential to reduce pesticide consumption, boost potato producer profitability, and reduce environmental risks.

Keywords: Computer Vision, disease classification, image processing, precision agriculture

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Introduction

Plant disease has become a serious threat to global food production and security. For example, it has been reported that over 800 million people globally lack adequate food and that approximately 10% of the world's food supply is lost due to plant disease, which has a significant impact on over 1.3 billion people living on less than $1 per day [1], [2]. Plant diseases cause 10–16% annual losses, costing $220 billion in global crop harvests (Society for General Microbiology, 2011). These statistics depict the ongoing food scarcity caused by plant disease damage to food production, which has become a global issue that should not be overlooked [3], [4]. To ensure an adequate supply of food for the world's rapidly rising population, agricultural production must be boosted by up to 70%. Nonetheless, a number of issues conspire against the provision and supply of food to fulfill the demands of the world's rising population. Furthermore, the agricultural sector remains critical to Africa's socioeconomic growth, accounting for 32% of GDP. Smallholder farmers provide around 80% of agricultural output and employ roughly 65% of the population. Low agricultural productivity is still a major problem in many African countries [5].

In terms of worldwide consumption, potato is the third most significant food crop [6]. Improved potato cultivation technologies have the ability to pull people out of poverty in Sub-Saharan Africa. The potato has a shorter cropping cycle and produces a large amount of yield per unit area quickly. On the other side, diseases including viruses, bacterial wilt (BW), late blight (LB), and early blight (EB) reduce the productivity of smallholder potato producers in Sub-Saharan Africa. Early blight and late blight caused by the fungi Alternaria solani and Phytophthora infestans, respectively, on potato plants have a negative effect on crop yield and quality. They are two leaf spot diseases that can cause from 30% to 75% of yield losses. [7]. To address these diseases, small-scale farmers typically use fungicides continuously; however, this practice encourages pesticide dependence and poses a threat to both human health and the environment [6]. Additionally, regulators like the European Union (EU) are establishing incredibly rigorous restrictions for the use of chemicals in agricultural products that are entering their markets [8].

Plant disease identification is crucial for enhancing agricultural productivity. Plants that are diseased frequently have obvious lesions or markings on their leaves, stems, blooms, or fruits. In general, it is possible to detect a disease using a certain visual pattern that is specific to each disease condition. On older (lower) leaves, early blight signs include tiny, rounded, or irregular dark-brown to black blotches. Over time, these patches may develop a 3/8-inch diameter and an angular shape [9]. The first indicators of late blight in the field are small, light to dark-green, spherical to irregularly shaped, water-soaked patches. These diseases typically start with the lowest leaves [10].

Potato blight control currently necessitates the uniform application of fungicides while ignoring regional dispersion, which not only raises production costs but also has a severe impact on the environment. As a result, an intelligent real-time classification system that can simply be integrated onto a robot to conduct targeted fungicide administration and discriminate sick plants from healthy ones could improve economic and environmental sustainability.

A review of the literature is provided in Section 2, and Section 3 details our experimental trial, imaging equipment, dataset, and CNN design. Section 3 discusses the results of each suggested CNN's real-time classification, and Section 4 concludes with some recommendations for further research.

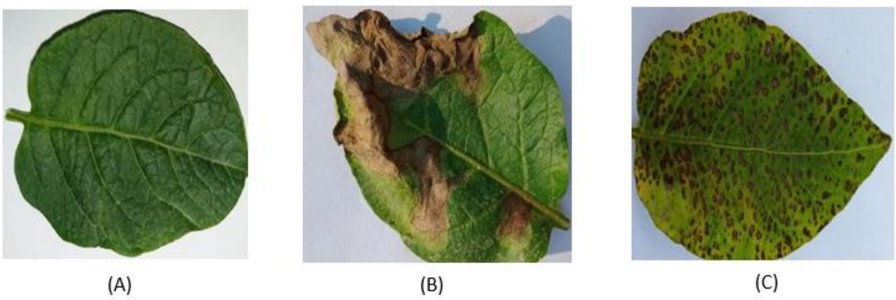


Figure1: Image from a dataset; healthy (A), late blight (B), and early blight (C)(provide a reference)

2 Related works

Deep learning is a subset of machine learning that is used to interpret visual data frquently through convolutional neural networks (CNNs). In agricultural applications, including crop classification and disease identification on plant leaves, CNNs are employed [11], [12]. Several studies have been undertaken to examine CNN's utility for disease identification. Transfer learning was utilized by S. E. Arnaud et al.[13] to compare six convolutional neural network architectures for disease detection in potato. The densnet121 model was the best, with an accuracy of 98.34% and an f1-score of 97.37%.

Using 300 potato photos from the PlantVillage dataset [14], Islam et al.[15] developed a classifier that could distinguish between healthy leaves and those damaged by late and early blight infections. Multiclass SVM was used to classify leaf images into three categories based on ten color and textural variables. The system's cross-validated accuracy was 93.7%. In contrast, the initial dataset includes 152 images of healthy potato leaves and 1,000 photographs of late and early blight, respectively. It would have been good to demonstrate the system's performance on a larger dataset. Sanjeev et al. 2021 [16] forecasted and classified disease in potato leaves using the Feed Forward Neural Network (FFNN) Model.

The accuracy of the model was found to be 96.5%. However, FFNN requires a significant amount of data and target pairings and a lengthy training period [17]. A CNN model for recognizing early and late potato blight infections was created by Lee et al. 2020 [18] and evaluated against VGG16 and VGG19. The researchers also used the unbalanced PlantVillage dataset. To detect late and early blight infections on potato leaves, Tiwari et al. 2020 [19] used enhanced (transfer learning) pre-trained models like VGG19. The model was improved to extract significant dataset patterns. In order to extract significant dataset features, the model was improved. Multiple classifier results showed that logistic regression performed significantly better than the others in terms of classification accuracy, obtaining 97.8% on the test dataset. For the purpose of identifying early blight infection in potatoes at different growth stages, Afzaal et al. [20] developed and compared three CNN models: GoogleNet, VGGNet, and EfficientNet, using the PyTorch framework. The outcomes demonstrated that the most successful model was EfficientNet. There is no study that suggests models for onsite disease identification of potato early and late blight. In this study, a large dataset will be used to investigate the real-time detection of potato blight. Furthermore, multiple studies have shown that data augmentation can improve CNN performance by using simple methods such as cropping, rotating, and flipping input images[21]–[23].

NVIDIA® Jetson Nano, the most recent addition to the Jetson series of embedded computing boards, is being used as an edge computing platform for machine learning(ML)inferencing, with significant research being undertaken in the fields of Internet of Things(IoT)and Machine Learning. V.Mazzia et al. [24] conducted research on real-time apple detection in order to assess apple yields and hence manage apple supplies. Previously reported machine vision algorithms for yield estimation had large computing power, required lengthy hardware setup, and were unsuitable for real-time apple identification due to weight and power constraints. Mazzia et al. used Jetson Nano for machine learning methods, which helped to accelerate

complex machine learning jobs. Because of the light weight, low power consumption, and form factor, yield estimation has become a plausible goal. The MuSHR, developed by S.S. Srinivasa et al. [25], is a substantially less expensive robotic race car, as well as an open-source platform for further study and education in the field. NVIDIA® 's cutting-edge Jetson Nano was used by V. Sati et al.2021[26] for face detection, identification, and emotion recognition. Face detection was performed using OpenCV's deep learning-based DNN face detector enhanced by a ResNet architecture to obtain more accuracy than previously built models.

3 Material and method

Fig.2 shows the proposed procedure for real-time identification of potato blight disease. The dataset was obtained from the internet.

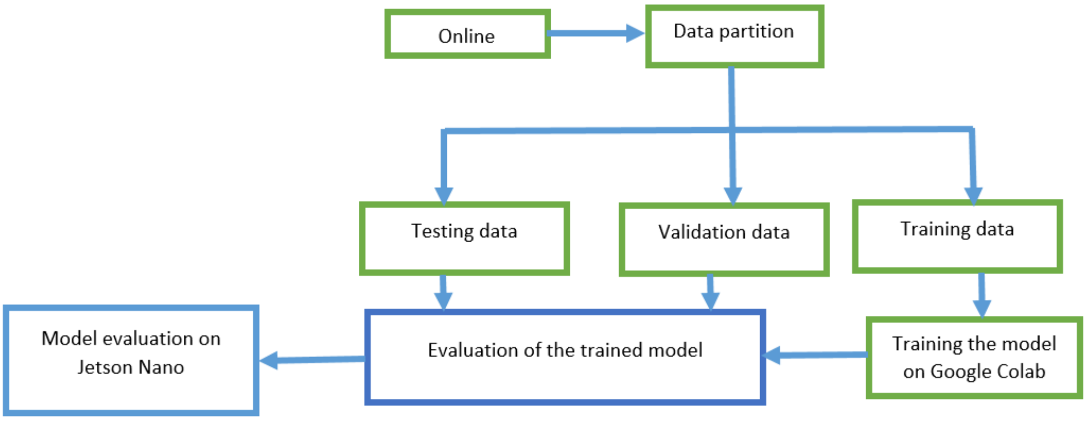


Figure 2: An overview of the proposed study's architecture

3.1 Dataset Description

In computer vision, gathering images relevant to a particular field of interest and training a classifier from scratch typically take some time. This problem can be solved using transfer learning by using a pre-trained model and changing the last few levels. Because the pre-trained model already learned the fundamental image properties from a much larger dataset, it is possible to achieve great results even with a small dataset. Using transfer learning in this investigation, DenseNet121 was employed since it has demonstrated good accuracy in previous research such as [13], [27]. For the training of the densenet121 model, 10% of the images present in the dataset were set aside for testing and evaluation using statistical measures (Tab.1). The remaining photos were used for 80% of the training and 10% of the validation of

the trained CNN. Before being converted to the Open Neural Network Exchange (ONNX) format for real-time disease classification on NVIDIA® Jetson Nano. On the training set, a number of data augmentation methods were applied to increase the dataset's diversity, including scaling, shear range, rotation, horizontal flip, brightness, zoom range, width shift, and height shift.

Table 1: Datasets organization for transfer learning to identify potato blight disease

Label	Training/Validation/ Testing	Image Used	Total Images
Late Blight	Training	1132	1434
	Validation	161	
	Testing	141	
Healthy	Training	816	1020
	Validation	102	
	Testing	102	
Early Blight	Training	1303	1628
	Validation	163	
	Testing	162	

3.2 DenseNet121 Architecture

Recent studies show that CNNs with shorter connections between input and output layers can be trained to be substantially deeper, more precise, and more effective. DenseNet links every layer to every other layer using the feed-forward method. Standard CNNs with L layers have L connections, one between each layer and the layer after it, whereas DenseNet's network has L (L + 1)/2 direct connections. Each layer uses the feature maps of the layers that came before it, and each layer uses the feature maps of the layers that came after it. Compared to classic CNN, DenseNet uses fewer parameters and enables more feature reuse, resulting in smaller models and superior performance on challenging datasets [28].

3.3 Experimental Framework

To train, modern CNN systems necessitate a large amount of computing power. As a result, GPU resources from Google Colab were used. Furthermore, transfer learning and evaluation of the trained CNN model were carried out using tools such as the Scikit-learn, PyTorch, and OpenCV. Hyperparameters are settings that are made before a machine learning model begins to learn. Tab.2 summarizes the values of hyperparameters such as learning rate, epochs, optimizer, and batch size employed in this work. The densenet121 model's performance in the

PyTorch framework was tested using the well-established statistical measures of precision, recall, and F-Score [29].

Table 2: Summarise of hyperparameter used for the training of DenseNet121 model

epoch	Learning rate	Batch size	*Optimizer*
100	0.01	32	*Adaptive moment estimation (Adam)*

3.4 Hardware architecture

To perform real-time categorization of potato blight disease, a number of electronic devices must be connected together as described in fig.2. This will allow the model to be evaluated for real-time classification.

The hardware for real-time potato blight classification is built with a Jetson Nano and certain standard components such as a battery, a DC to DC step down converter, a 3 s battery management system (BMS), and a WIMAXIT 15.6 touch screen. In this experiment, 12 lithium batteries were connected in series and parallel to generate a battery with a voltage of 12.6 volts and a current of 31.2 amps. When the battery died, the 3s BMS 12.6v and 20A were utilized to charge it.The DC to DC step down converter was used to reduce the battery's 12.6 volts to 5.2 volts and 6A to power the Jetson nano and touch screen. Some components were produced for this investigation to accommodate the Jetson Nano, battery, BMS, and step down converter, as shown in fig.3.

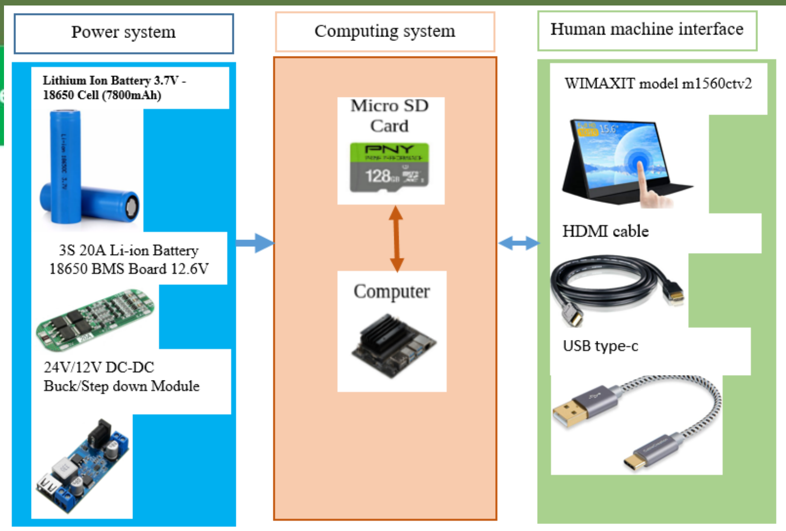


Figure 3: Overview of the hardware components

4. Result and Discussion

The performance of the recommended model was evaluated using a set of quantitative criteria including accuracy, precision, recall, and F1score. The findings are summarized in Tab.3.

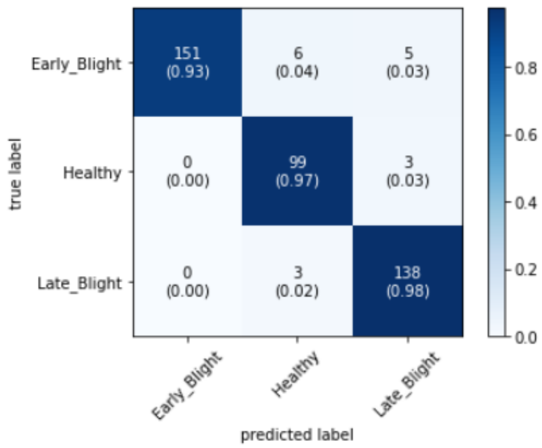
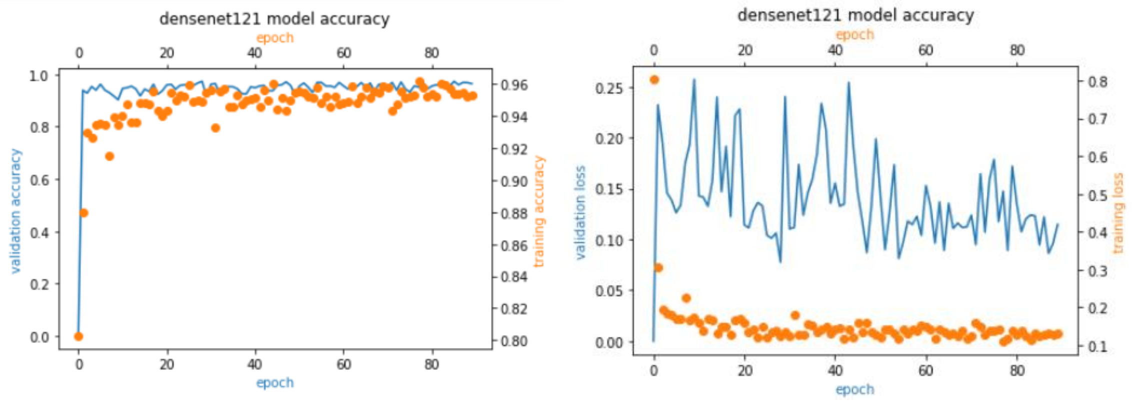


Table 3: Performance evaluation of

epoch	accuracy	precision	recall	specificity	F1-score
90	97.33%	95.76%	96.34%	98.05%	96.05%

Figure 4: Plots confusion matrix

Over 90 epochs of training, the highest validation accuracy of 97.32% was achieved, with a high training accuracy of 96.17 percent. On average, validation accuracy was found to be 94 percent. This is a good indicator of how well the deep learning model classified the data. The plots of train and test accuracy and loss against the epochs in Fig. 6 provide a visual representation of model convergence speed. The model appears to have stabilized at 20 epochs, and the metrics have not improved significantly in the last 10 epochs. The results suggest that the model performs well on the dataset and that it may be used to clas sify the potato blight illness with minimal resources.



Figugre 5: Plot confusion matrix of the best model over the test data.

The potato blight recognition system was trained and then tested on a live webcam stream connected to the Jetson Nano, and it correctly identified the disease on potato leaves as shown in fig.6.

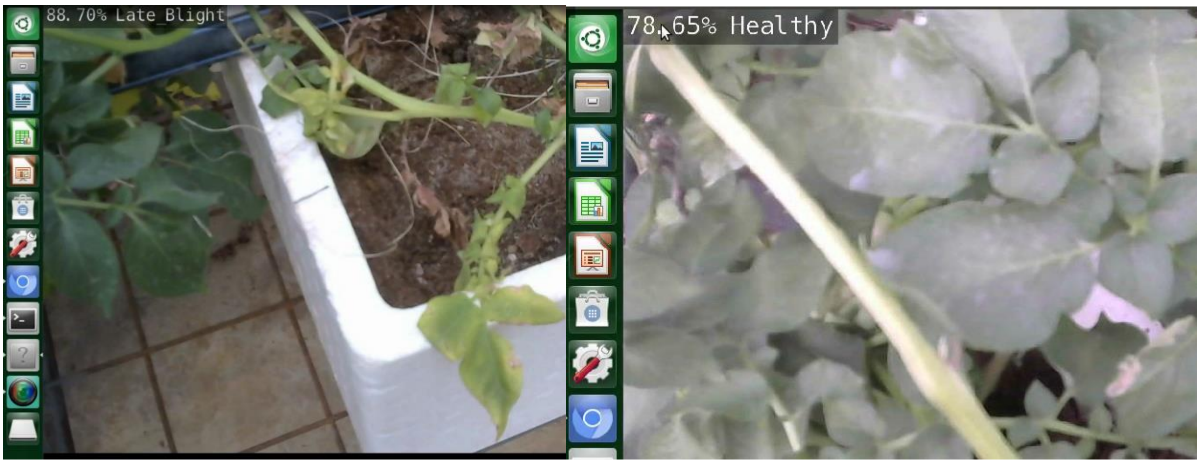


Figure 6: Sample of potato blight disease recognition result

The outcomes of the process of identifying potato blight disease using the densenet121 model in the Jetson Nano NVIDIA are presented to support the research findings. Following the completion of the potato disease identification testing in the greenhouse, the variables such as power consumption, accuracy, and processing time were all examined. The power consumption of the jetson nano when runing the real time potato disease classification ranges from 0 to 32W. The average processing time recorded was 45.7ms with an average of 28 frame per second.

5.Conclusion

On the Jetson Nano, the applicability of a convolution neural network, specifically the densenet121 model, for real-time disease classification was investigated. Given the Jetson nano's low cost, learned models from any deep learning framework can be imported into TensorRT, allowing neural network models (Densnet121 for this study) trained in all major frameworks to be tuned and calibrated for lower precision with high accuracy. Overall, the accuracy findings, coupled with the statistical measure for the densenet121 model, the inference time, and the power consumption of the Jetson Nano, demonstrated that the densenet model may be used and integrated to develop a smart sprayer for targeted fungicide spraying in potato fields.

References:

[1] S. P. Mohanty, D. P. Hughes, and M. Salathé, “Using deep learning for image-based plant disease detection,” *Front. Plant Sci.*, vol. 7, no. September, pp. 1–10, 2016, doi: 10.3389/fpls.2016.01419.

[2] P. Christou and R. M. Twyman, “The potential of genetically enhanced plants to address food insecurity,” pp. 23–42, 2004, doi: 10.1079/NRR200373.

[3] W. Ng, “White discoloration on leaves and flower-like outgrowth on stem : A new species or hormonal disequilibrium,” pp. 1–6, 2016.

[4] R. N. Strange and P. R. Scott, “Plant Disease : A Threat to Global Food Security P LANT D ISEASE : A Threat to Global Food Security,” no. February 2005, 2016, doi: 10.1146/annurev.phyto.43.113004.133839.

[5] P. F. Ribeiro and A. V. C. Rodriguez, “Emerging advanced technologies to mitigate the impact of climate change in Africa,” *Plants*, vol. 9, no. 3, pp. 1–14, 2020, doi: 10.3390/plants9030381.

[6] A. Devaux, P. Kromann, and O. Ortiz, “Potatoes for Sustainable Global Food Security,” *Potato Res.*, vol. 57, no. 3–4, pp. 185–199, 2014, doi: 10.1007/s11540-014-9265-1.

[7] O. M. Olanya *et al.*, “Epidemiology and population dynamics of Phytophthora infestans in Sub-Saharan Africa: Progress and constraints,” *African Crop Sci. J.*, vol. 9, no. 1, 2001, doi: 10.4314/acsj.v9i1.27638.

[8] A. Brancato *et al.*, "Reporting data on pesticide residues in food and feed according to Regulation (EC) No 396/2005 (2017 data collection)," *EFSA J.*, vol. 16, no. 6, 2018, doi: 10.2903/j.efsa.2018.5285.

[9] M. J. Bauske, A. P. Robinson, and N. C. Gudmestad, "Early Blight in Potato — Publications," *North Dekota State Univ. Extention*, no. June, p. 8, 2018, [Online]. Available: https://www.ag.ndsu.edu/publications/crops/early-blight-in-potato.

[10] A. Robinson, "Late Blight in Potato," *ResearchGate*, no. May, p. 4, 2017, [Online]. Available: www.ag.ndsu.edu.

[11] N. Rudakov, T. Eerola, L. Lensu, H. Kälviäinen, and H. Haario, "Detection of Mechanical Damages in Sawn Timber Using Convolutional Neural Networks," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 11269 LNCS, pp. 115–126, 2019, doi: 10.1007/978-3-030-12939-2_9.

[12] S. Ashraf, I. Kadery, A. A. Chowdhury, T. Z. Mahbub, and R. M. Rahman, "Fruit Image Classification Using Convolutional Neural Networks," *Int. J. Softw. Innov.*, vol. 7, no. 4, pp. 51–70, 2019, doi: 10.4018/IJSI.2019100103.

[13] S. E. Arnaud, N. Rehema, S. Aoki, and M. L. Kananu, "Comparison of Deep Learning Architectures for Late Blight and Early Blight Disease Detection on Potatoes," *Open J. Appl. Sci.*, vol. 12, no. 05, pp. 723–743, 2022, doi: 10.4236/ojapps.2022.125049.

[14] D. P. Hughes and M. Salathe, "An open access repository of images on plant health to enable the development of mobile disease diagnostics," 2015, [Online]. Available: http://arxiv.org/abs/1511.08060.

[15] M. Islam, A. Dinh, K. Wahid, and P. Bhowmik, "Detection of potato diseases using image segmentation and multiclass support vector machine," *Can. Conf. Electr. Comput. Eng.*, pp. 8–11, 2017, doi: 10.1109/CCECE.2017.7946594.

[16] K. Sanjeev, N. K. Gupta, W. J. Jeberson, and S. Paswan, "Early Prediction of Potato Leaf Diseases Using ANN Classifier," *Orient. J. Comput. Sci. Technol.*, vol. 13, no. 0203, pp. 129–134, 2021, doi: 10.13005/ojcst13.0203.11.

[17] A.-N. Sharkawy, "Principle of Neural Network and Its Main Types: Review," *J. Adv. Appl. Comput. Math.*, vol. 7, no. 1, pp. 8–19, 2020, doi: 10.15377/2409-5761.2020.07.2.

[18] T. Y. Lee, J. Y. Yu, Y. C. Chang, and J. M. Yang, "Health Detection for Potato Leaf with Convolutional Neural Network," *Indo - Taiwan 2nd Int. Conf. Comput. Anal.*

Networks, Indo-Taiwan ICAN 2020 - Proc., pp. 289–293, 2020, doi: 10.1109/Indo-TaiwanICAN48429.2020.9181312.

[19] D. Tiwari, M. Ashish, N. Gangwar, A. Sharma, S. Patel, and S. Bhardwaj, "Potato Leaf Diseases Detection Using Deep Learning," *Proc. Int. Conf. Intell. Comput. Control Syst. ICICCS 2020*, no. Iciccs, pp. 461–466, 2020, doi: 10.1109/ICICCS48265.2020.9121067.

[20] H. Afzaal *et al.*, "Detection of a potato disease (Early blight) using artificial intelligence," *Remote Sens.*, vol. 13, no. 3, pp. 1–17, 2021, doi: 10.3390/rs13030411.

[21] L. Perez and J. Wang, "The Effectiveness of Data Augmentation in Image Classification using Deep Learning," 2017, [Online]. Available: http://arxiv.org/abs/1712.04621.

[22] E. Hupe, "INCREASING DEEP LEARNING MELANOMA CLASSIFICATION BY CLASSICAL AND EXPERT KNOWLEDGE BASED IMAGE TRANSFORMS."

[23] Y. Xu *et al.*, "Improved relation classification by deep recurrent neural networks with data augmentation," *COLING 2016 - 26th Int. Conf. Comput. Linguist. Proc. COLING 2016 Tech. Pap.*, no. January, pp. 1461–1470, 2016.

[24] V. Mazzia, A. Khaliq, F. Salvetti, and M. Chiaberge, "Real-time apple detection system using embedded systems with hardware accelerators: An edge AI application," *IEEE Access*, vol. 8, pp. 9102–9114, 2020, doi: 10.1109/ACCESS.2020.2964608.

[25] S. S. Srinivasa *et al.*, "MuSHR: A Low-Cost, Open-Source Robotic Racecar for Education and Research," no. August, 2019, [Online]. Available: http://arxiv.org/abs/1908.08031.

[26] V. Sati, S. M. Sánchez, N. Shoeibi, A. Arora, and J. M. Corchado, "Face detection and recognition, face emotion recognition through nvidia jetson nano," *Adv. Intell. Syst. Comput.*, vol. 1239 AISC, no. June 2021, pp. 177–185, 2021, doi: 10.1007/978-3-030-58356-9_18.

[27] E. C. Too, L. Yujian, S. Njuki, and L. Yingchun, "A comparative study of fine-tuning deep learning models for plant disease identification," *Comput. Electron. Agric.*, vol. 161, no. October 2017, pp. 272–279, 2019, doi: 10.1016/j.compag.2018.03.032.

[28] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," *Proc. - 30th IEEE Conf. Comput. Vis. Pattern Recognition, CVPR 2017*, vol. 2017-Janua, pp. 2261–2269, 2017, doi: 10.1109/CVPR.2017.243.

[29] M. Sokolova and G. Lapalme, "A systematic analysis of performance measures for classification tasks," *Inf. Process. Manag.*, vol. 45, no. 4, pp. 427–437, 2009, doi: 10.1016/j.ipm.2009.03.002.