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Identification of Corn Leaf Diseases Comprising of Blight, Grey Spot and Rust Using DenseNet-201

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ABSTRACT

Corn is a vital commodity in Malaysia because it is a key component of animal feed. The retention of the wholesome corn yield is essential to satisfy the rising demand. Like other plants, corn is susceptible to pathogens infection during the growing period. Manual observation of the diseases nevertheless takes time and requires a lot of work. The aim of this study was to propose an automatic approach to identify corn leaf diseases. The dataset used comprises of the images of diseased corn leaf comprising of blight, grey spot and rust as well as healthy corn leaf in YCbCr colour space representation. The DenseNet-201 algorithm was utilised in the proposed method of identifying corn leaf diseases. The training and validation analysis of distinctive epoch values of DenseNet-201 were also used to validate the proposed method, which resulted in significantly higher identification accuracy. DenseNet-201 succeeded 95.11% identification accuracy and it outperformed the prior identification methods such as ResNet-50, ResNet-101 and Bag of Features. The DenseNet-201 also has been validated to function as anticipated in identifying corn leaf diseases based on the algorithm validation assessment.

Keywords: Blight, corn, DenseNet-201, grey spot, rust

INTRODUCTION

After wheat and rice, corn is the world's third most important food crop (Foley *et al.*, 2019). Corn has also been used for human and animal consumption. Corn is an important commodity in Malaysia because it is the main component of animal feeds (Iqbal *et al.*, 2019). Aside from that, Malaysia is currently a net importer of corn because domestic production is insufficient to meet the increased demand of the livestock industry (Amna *et al.*, 2019). As a result, the study of diseases detection in corn leaf is very important and significant for Malaysia to prevent negative impacts and other adverse effects.

Multiple cases of corn leaf diseases such as blight, grey spot, and rust were reported in Peninsular Malaysia and Sabah between 1953 and 2017. Sijam *et al*. (2017) found the long lesions measuring 2 – 3 cm long with blighted zones, cigar-shaped and blighted portions formed by fungus *Setosphaeria turcica* from samples collected from farms in Titi Gantong and Lembah Bertam of Perak and Pahang, respectively. From that report, the presence of corn leaf blight disease in Malaysia was confirmed.

Besides that, The Checklist of Fungus of Malaysia (Lee *et al*., 2012) reported numerous distribution of fungus *Cercospora zeae-maydis* in Peninsular Malaysia associated with grey leaf spot of corn. Report on infection of corn grey leaf spot in Peninsular Malaysia has been discovered since 1953 (Thompson & Johnson, 1953).

The Checklist of Fungus of Malaysia (Lee *et al*., 2012), also reported that there are plentiful distribution of fungus *Puccinia sorghi* associated with corn leaf rust in Peninsular Malaysia and Sabah. Reports of infection by corn leaf rust in Peninsular Malaysia have been made since the year of 1953, while the infection in Sabah is made in the year of 1976 and 1980.

For the early diagnosis of plant leaf diseases, there were numerous traditional and modern practices. Without the use of mechanical tools, the traditional method relied solely on human visual assessment which was difficult to be carried out. Lately, image processing has emerged as a promising approach for identifying the disease because it is timelier and meritorious. Recently, with the development of automated diseases diagnosing models, computer vision and pattern recognition in particular, have accomplished enormous strides in plant leaf disease identification (Mohanty *et al*., 2016). There are variety of existing automated plant leaf disease image identification methods for identifying plant leaf diseases. Table 1 presents the limitations and accuracies of the previous identification methods.

Table 1. Limitations and accuracies of the existing methods of plant leaf identification

Existing method	Limitation	Accuracy (%)
ResNet-50 (Wang *et al*., 2017)	Vulnerable to noise and emit an extraneous input (Maeda-Gutiérrez *et al*., 2020).	83.50
ResNet-50 (Gawade, 2021)	Intensified architectural complexity (Maeda-Gutiérrez *et al*., 2020).	90
ResNet-101 (Fuentes *et al*., 2017)	Underachieve in composite and classes of high-intra deviation (Alzubaidi *et al*., 2021).	41.30 – 80.30
ResNet-101 (Yang & Xu, 2021)	Segmentation accuracy decreases as the network grows deeper (Alzubaidi *et al*., 2021).	86.40
Bag of Features (Aravind *et al*., 2018)	Low fault forbearance (Hiba *et al*., 2016).	83.70
Bag of Features (Santiago *et al*., 2019)	Consequential trajectories with majority of invalid significances and scant (Hiba *et al*., 2016).	71.60

Although a few of them have good accuracies but they have several limitations based on the findings in the literature as shown in Table 1. Thus, DenseNet-201 identification algorithm is proposed in this paper to identify corn leaf diseases. DenseNet-201, which has 201 layers deep and pretrained to identify images into 1000 object categories using ImageNet database (Attallah, 2021). The network is retrained to execute a new image identification job in this study. DenseNet-201 models are built with several parallel layer skips that aid in the training of deeper network architectures to identify corn leaf diseases. DenseNet-201 encompasses a concatenate convolutional network that extricated it from other identifier algorithms, which upsurges variation in the input of subsequent layers and enriches efficiency (Noh, 2021). The layers between two adjacent blocks are implied to as transition layers or concatenate convolutional neural network layers. Furthermore, DenseNet-201 contains four dense blocks and three transition layers that enhance the competency of the identification.

The corn leaf images that will be utilised as input in image identification are in the YCbCr colour space. The actual colour displayed is determined by the RGB colourants used to present the corn leaf images, but these RGB are inefficient as a representation for storage and transmission due to their high mutual redundancy (Wang *et al*., 2018). YCbCr distinguishes between a luma (Y) component that can be stored in high resolution or transmitted at high bandwidth and two chroma components (Cb and Cr) that can be bandwidth-reduced, sub-sampled, compressed, or otherwise treated separately to improve algorithm efficiency. The primary colours corresponding roughly to red, green, and blue are processed into perceptually meaningful information in YCbCr, a practical approximation to colour processing and perception uniformity. This allows subsequent image processing, transmission, and storage to perform operations and introduce errors in perceptually meaningful ways.

MATERIALS AND METHODS

Framework of Research

In this study, the identification of corn leaf diseases was carried out by utilising computer vision algorithm. Figure 1 displays the overall fundamental steps taken to develop algorithms to detect corn leaf diseases.

Firstly, image dataset was obtained from PlantVillage Image website. Then, for image pre-processing, colour space transformation from RGB to YCbCr was implemented. Data augmentation via vertical flipping was applied to expand the corn leaf image dataset. For corn leaf diseases identification, DenseNet-201 algorithm was used. Lastly, plot performance, regression model plot, error histogram, training state and confusion matrix were applied to authenticate the DenseNet-201 algorithm.

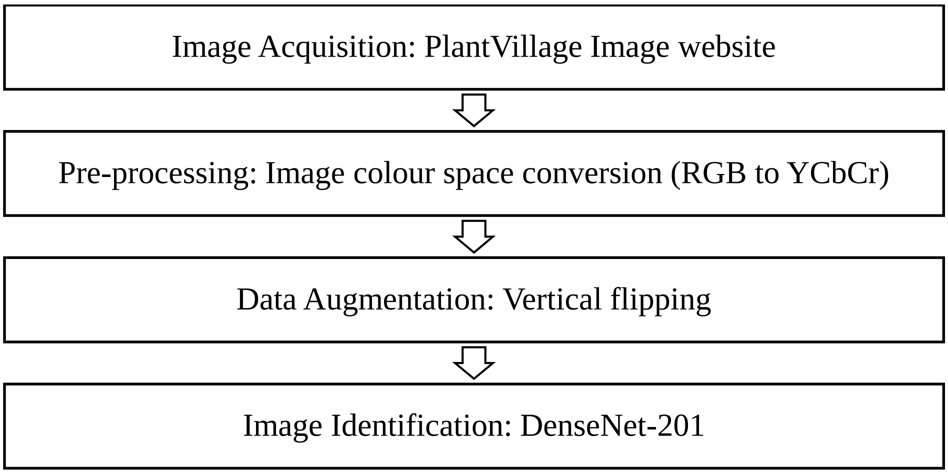
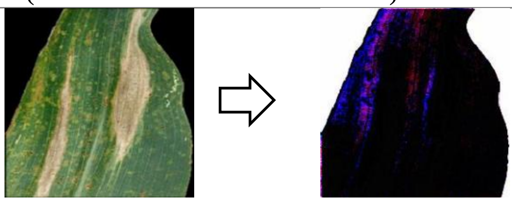
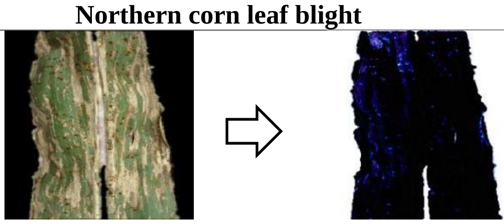
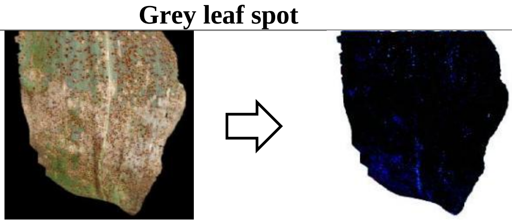
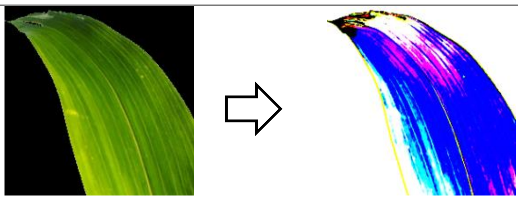


Figure 1. Framework to develop corn leaf diseases identification algorithm

Table 2. Information on dataset of diseased and healthy corn leaf images

Type of Disease (Conversion from RGB to YCbCr)	Total Images	Size of Images	Pixel Resolution
 **Northern corn leaf blight**	984	227×227	224×224
 **Grey leaf spot**	508	227×227	224×224
 **Common rust**	1192	227×227	224×224
 **Healthy**	1162	227×227	224×224

This study was performed using MATLAB R2018b software with the following computer specifications:

- Computer System: Laptop Computer, Acer Aspire E5-471
- Microprocessor: Intel® Core™ i3-4030U CPU
- Microprocessor Clock Speed: 1.90GHz
- Random Access Memory (RAM): 6.00GB
- Operating System: Windows 8.1 Single Language with Bing

Image Acquisition and Pre-processing

This study makes use of the corn leaf dataset obtained primarily from https://plantvillage.psu.edu/ website. This website serves as a platform for anyone to interchange their agricultural comprehension with others who cultivate plant-based foods all across the globe. Penn State University in the United States and École Polytechnique Fédérale de Lausanne (EPFL) in Switzerland act as a team to propagate this website (Hughes & Salathé, 2016). Table 2 also summarises the total number of every sort of corn leaf diseases used in this study as well as their sizes and resolutions.

Data Augmentation and Image Identification

Based on the images in the dataset as shown in Table 2, data augmentation technique was performed to artificially grow the size of a training dataset by generating the amended versions of images in the dataset. As illustrated in Figure 2, through vertical flipping technique, the training data is diversified.

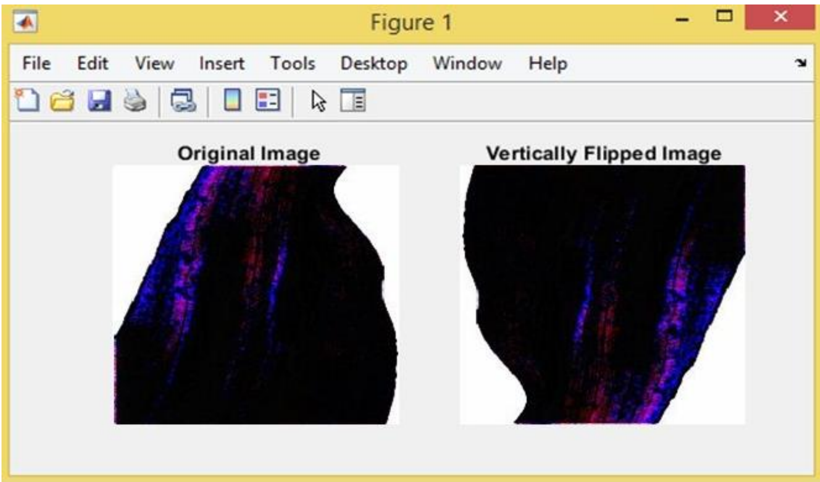


Figure 2. Data augmentation (vertical flipping) of corn leaf image

Following data augmentation, the overall image is increased to 4354, for the use of image identification employing DenseNet-201 as proposed in the subsequent stage. The first step in DenseNet-201 image classification is the transfer learning process. Using transfer learning, a convolutional neural network is retrained to identify corn leaf diseases. Pretrained network is fine-tuned to make training the dataset speedier and easier than starting from scratch with randomly initialised weights (Kandel & Castelli, 2020). DenseNet-201 training images account for 90% of the total number of each type of leaf diseases. DenseNet-201 with different epoch values, 5, 10, 15, 20, 25 and 30 are experimented and the validation results are recorded. Figure 3 depicts a DenseNet-201 network for identifying the type of corn leaf diseases.

Table 3. Properties of the transfer learning and hyperparameter fine tuning of DenseNet-201

Parameter	**Setting**
Training data validation	90%
Batch size	224
Learning rate	0.1 throughout
Hyperparameter, *k*	32
Channel features	32 (1×1 to 3×3 conv)
Optimizer	Stochastic gradient descent with momentum (SGDM)

Convolution and pooling layers used to modify the feature map sizes of corn leaf images. The properties of the transfer learning and hyperparameter fine tuning of DenseNet-201 network layer applied here are tabulated in Table 3. After that, the identification accuracy of using DenseNet-201 was compared to detection accuracies achieved by the existing methods. Following that, the performance of DenseNet-201 was validated through precision, recall and F1 score using Eq. (1), Eq. (2) and Eq. (3).

$$Precision = \frac{True\ Positives}{(True\ Positives + False\ Positives)} \quad (1)$$

Where,
True Positives = all the true matches
True Positives + False Positives = all the re-identified matches

$$Recall = \frac{True\ Positives}{(True\ Positives + False\ Negatives)} \quad (2)$$

Where,
True Positives = all the true matches
True Positives + False Negatives = all the real matches

$$F1\ score = 2 \times \frac{(Recall \times Precision)}{(Recall + Precision)} \quad (3)$$

RESULTS AND DISCUSSION

Validation Accuracy of DenseNet-201

Table 4 displays the training validation accuracy for the DenseNet-201 network when various epoch values were applied.

Table 4. Summary of validation results of DenseNet-201

Value of e*poch*	Training Validation Accuracy (%)
5	99.46
10	99.78
15	99.80
20	99.86
25	**99.90**
30	99.82

Network of DenseNet-201 with epoch value of 25 delivered the highest training validation accuracy (99.90%). Therefore, the network was trained with 25 epochs and the trained model is used for inference or testing. Based on Table 4, the validation accuracy increases from epoch value 5 to 25 but decreases when 30 epoch is employed. This is because when the epoch value is too large, it is deficient because the network overfits to the training data (Alzubaidi *et al.*, 2021). Figure 4 demonstrates DenseNet-201's training accuracy and training loss.

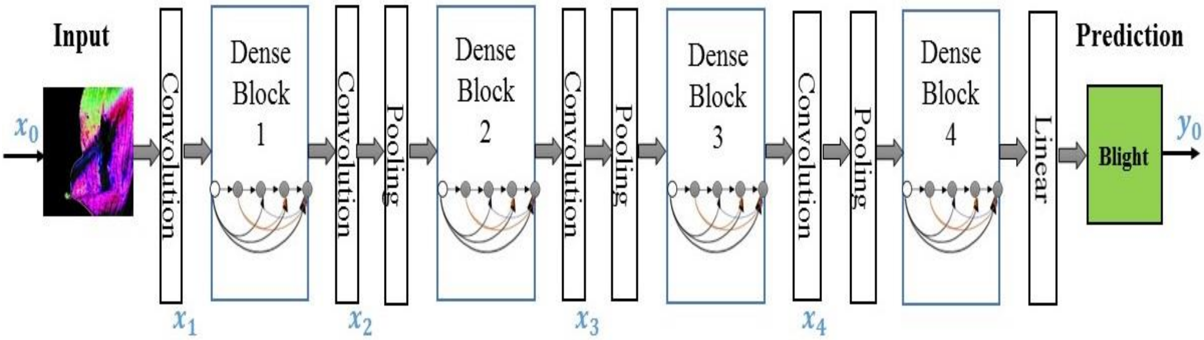


Figure 3. DenseNet-201 with four dense blocks

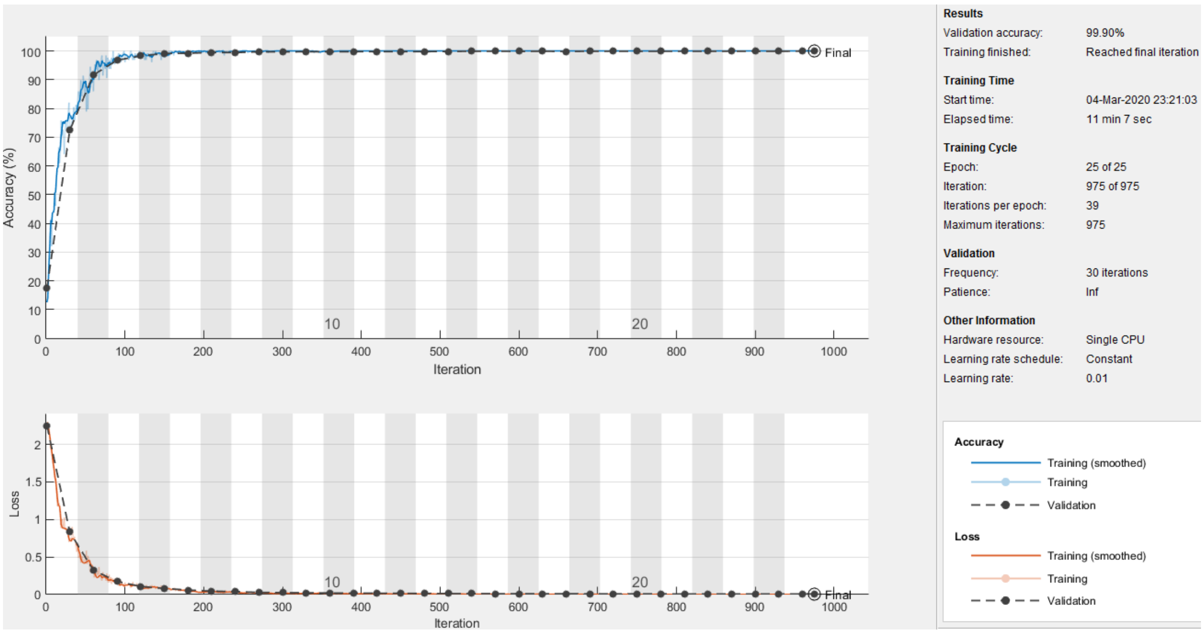


Figure 4. Training accuracy and training loss of DenseNet-201 for epoch value of 25

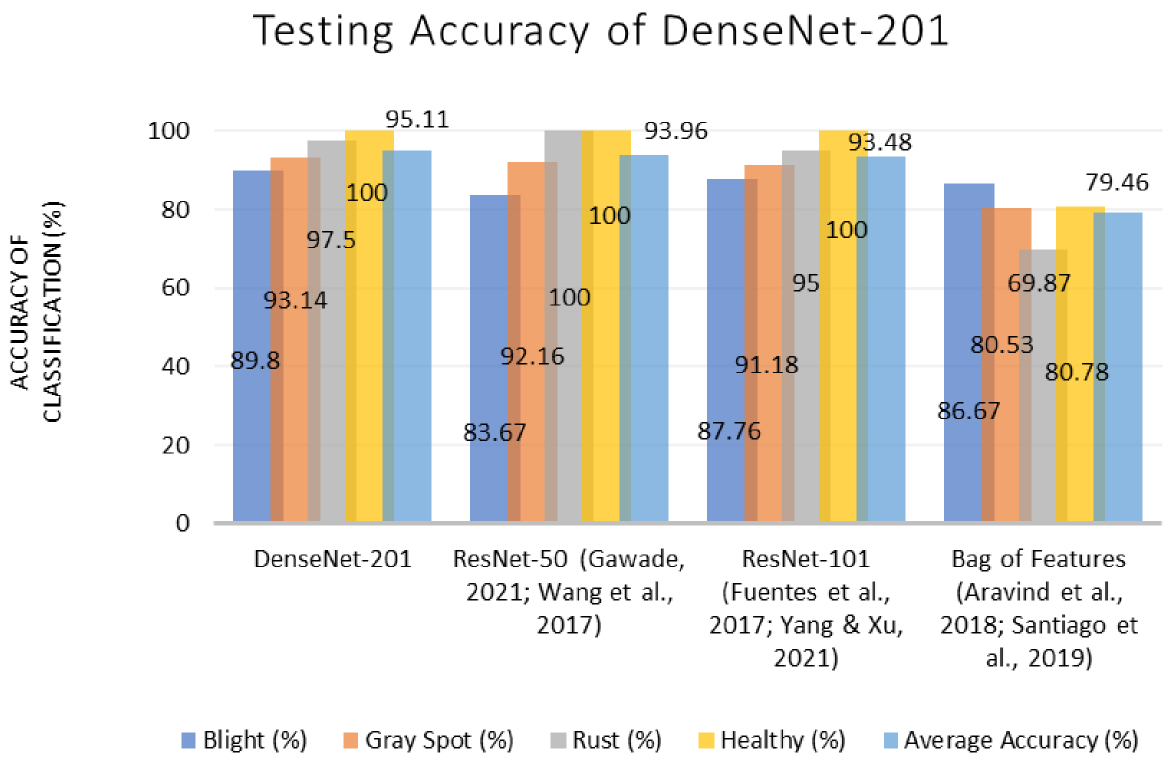


Figure 5. Testing accuracy of DenseNet-201 and existing methods of image identification

Testing Accuracy of DenseNet-201

Figure 5 shows that the proposed method of DenseNet-201 generated the best results with testing accuracy of 95.11% versus the existing methods of ResNet-50 (93.96%), ResNet-101 (93.48%), and Bag of Features (79.46%). DenseNet-201 has three transition layers, it yielded the highest testing accuracy. Briefer connections between layers adjacent to the input and those close to the output permit DenseNet-201 to be significantly profounder, more precise, and competent to train (Huang *et al*., 2019). Aside

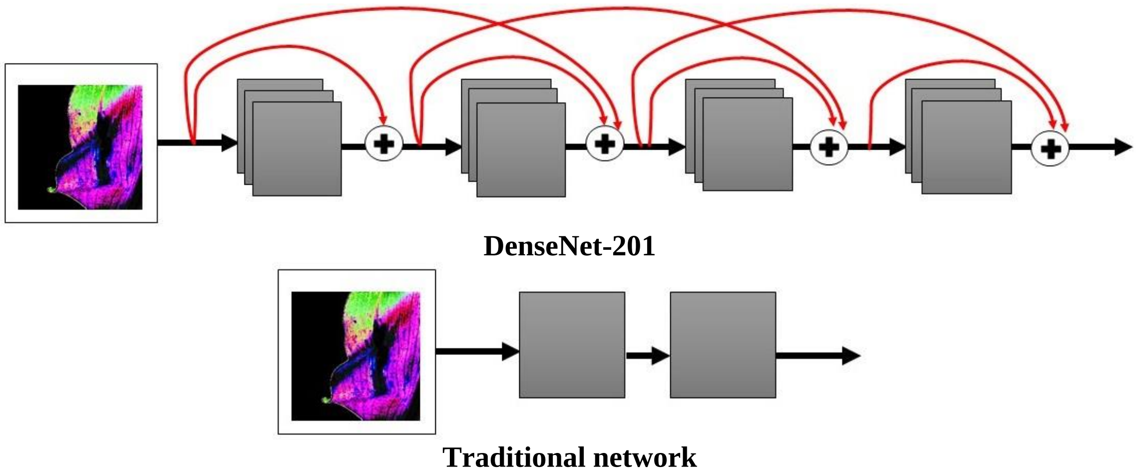


Figure 6. Comparison of DenseNet-201 and traditional network

from that, DenseNet-201's architecture contains skip connections which differ it from traditional convolutional networks as illustrated in Figure 6.

DenseNet-201 is connected in L connections, one between each layer and its subsequent layer, and each layer to the next layer in a feed-forward fashion (Chauhan *et al*., 2020), which is a more direct and efficient connection. The feature-maps of all preceding layers are employed as inputs for each layer, and its own feature-maps used as inputs to all subsequent layers. DenseNet-201 has several compelling plusses, like dismissal of the vanishing-gradient obstruction, better-quality feature propagation, feature reuse, and a substantial diminution in the number of parameters (Xie *et al*., 2021). DenseNet-201 also proves its dense connectivity to ensure maximum information flow between network layers via its architecture, which connects all layers directly with each other (Ji *et al*., 2021).

ResNet-50 and ResNet-101 used more than two layers, resulting in lower accuracy when compared to DenseNet-201. This is due to the fact that information augmented to the network amplifies as the layer increases, as each layer has its own information weights. For Bag of Features, because it defies the spatial relationships among the patches (Hiba *et al.*, 2016), which are imperative in image representation, it served the lowest accuracy. Other than that, the factor that impacted to the poor performance of Bag of Features is the vocabulary size exercised in this study, which is 1000. This is because the larger the size vocabulary, the better; however, 1000 is customarily used for texture and image classifications (Kupidura, 2019). The confusion matrix of the DenseNet-201 model is shown in Table 6 to certify that the proposed algorithm is acceptable, compliant, and that all possible legal inputs are correctly responded to through the discovery of the value of precision, recall, and F1 score.

The weighted precision of DenseNet-201 produced is 92.52%, explaining that the proportion of data points of the DenseNet-201 model used in this study is pertinent to the actual proportion of data points expected to separate each four classes of diseased corn leaf images. Weighted recall obtained is 91.48%. This high achieved value of weighted recall implies that the total number of types of corn leaf diseases are accurately classified by DenseNet-201. For weighted F1 score or harmonic mean between precision and recall, 91.35% is accomplished. This infers that the DenseNet-201 algorithm is highly precise and robust. It is also clear from the comparison DenseNet-201 is particularly efficient at identifying corn leaf diseases with higher weighted precision than weighted recall produced.

Table 6. Confusion matrix of DenseNet-201 model

Confusion Matrix		Predicted: Class 1 Blight	Predicted: Class 2 Grey Spot	Predicted: Class 3 Healthy	Predicted: Class 4 Rust	False Negative (FN)	Recall (%)	F1 Score (%)
Actual	**Class 1** Blight	70	24	0	4	28	71.43	81.87
Actual	**Class 2** Grey Spot	2	98	0	2	4	96.08	85.96
Actual	**Class 3** Healthy	0	0	116	0	0	100	100
Actual	**Class 4** Rust	1	4	0	114	5	95.80	95.40
	False Positive (FP)	3	28	0	6	**Weighted Precision = 92.52 %**; **Weighted Recall = 91.48 %**		
	Precision (%)	95.89	77.78	100	95.00	**Weighted F1 Score = 91.35 %**		

CONCLUSION

A comparison of the DenseNet-201 and other existing identification methods such as ResNet-50, ResNet-101, and Bag of Features reveals that the DenseNet-201 outperforms the existing methods by achieving 95.11% testing accuracy to identify corn leaf diseases. Aside from that, the model validation result discloses that DenseNet-201 performs efficiently as intended. Therefore, the proposed DenseNet-201 method is an effective method to identify corn leaf diseases.

The research objectives have been achieved but there are some directions for future research that can be pursued. The data that has been analysed and modelled is solely based on images of diseased corn leaves, larger datasets and various types of plant leaves should be used in future experiments for generalisation of the proposed algorithm. The dataset used in this study is acquired from the PlantVillage Image website captured using a Sony DSC - Rx100/13 20.2-megapixel camera with a resolution of 256×256 (96 dpi). Despite using this publicly accessible dataset, a more advanced camera can be utilised in future research with higher pixel count, stable, low-noise, and higher-quality. Future research should also consider inputs (images or signals) from other parts of a plant such as leaf veins, such as stems, fruits, and flowers, which have received little attention from researchers. Then, all these features can be blended to enhance disease identification accuracy of the model.

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REFERENCES

Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., Santamaría, J., Fadhel, M.A., Al-Amidie, M. & Farhan, L. (2021). Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. *Journal of Big Data*, 8(1): 28–49.

Amna, N., Mohammad, A., Rabu, M.R., Alif, M. & Hifzan, M. (2019). An overview of the grain corn industry in Malaysia. *Food and Fertilizer Technology Center Agricultural Policy Platform*, 8(2): 1–7.

Aravind, K.R., Raja, P., Mukesh, K.V, Aniirudh, R., Ashiwin, R. & Szczepanski, C. (2018). Disease classification in maize crop using bag of features and multiclass support vector. *International Conference on Inventive Systems and Control*, 10(2): 1191–1196.

Attallah, O. (2021). CoMB-Deep: Composite deep learning-based pipeline for classifying Childhood Medulloblastoma and its classes. *Frontiers in Neuroinformatics*, 15(2): 1-19.

Chauhan, T., Palivela, H. & Tiwari, S. (2020). Optimization and fine-tuning of DenseNet model for classification of Covid-19 cases in medical imaging. *International Journal of Information Management Data Insights*, 1(7): 1-13.

Foley, D.J., Thenkabail, P.S., Aneece, I.P., Pardhasaradhi, G., Oliphant, A.J., Foley, D.J., Thenkabail, P.S., Aneece, I.P. & Pardhasaradhi, G. (2019). A meta-analysis of global crop water productivity of three leading world crops (wheat, corn, and rice) in the irrigated areas over three decades. *International Journal of Digital Earth*, 28(5): 1–37.

Fuentes, A., Yoon, S., Kim, C.S. & Park, S.D. (2017). A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition. *International Journal of Sensors*, 17(2): 1–21.

Gawade, A. (2021). Early-stage apple leaf disease prediction using deep learning. *Bioscience Biotechnology Research Communications*, 14(5): 40–43.

Hiba, C., Hamid, Z. & Omar, A. (2016). Bag of features model using the new approaches: a comprehensive study. *International Journal of Advanced Computer Science and Applications*, 7(1): 226–234.

Huang, G., Liu, Z., Pleiss, G., Van Der-Maaten, L. & Weinberger, K.Q. (2019). Convolutional networks with dense connectivity. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 3(1): 1–12.

Hughes, D.P. & Salathé, M. (2016). An open access repository of images on plant health to enable the development of mobile disease diagnostics. *Computer and Society*, 11(1), 2–13.

Iqbal, A., Qudoos, A., Çetingül, I.S., Shah, S.R.A. & Bayram, I. (2019). Looking at some animal feeds with respect to halal concept. *Journal of Animal Science and Products*, 2(1): 46–53.

Ji, L., Zhang, J., Zhang, C., Ma, C., Xu, S. & Sun, K. (2021). CondenseNet with exclusive lasso regularization. *Neural Computing and Applications*, 7(2): 1–15.

Kandel, I. & Castelli, M. (2020). Transfer learning with convolutional neural networks for diabetic retinopathy image classification. A review. *Applied Sciences*, 10(6): 1–24.

Kupidura, P. (2019). The comparison of different methods of texture analysis for their efficacy for land use classification in satellite imagery. *Remote Sensing*, 11(10): 1–20.

Lee, S.S., Alias, S.A., Jones, E.G.B., Zainuddin, N. & Chan, H.T. (2012). *Checklist of Fungi of Malaysia*. Kepong: Forest Research Institute Malaysia,

Maeda-Gutiérrez, V., Galván-Tejada, C.E., Zanella-Calzada, L.A., Celaya-padilla, J.M., Galván-tejada, J.I., Gamboa-rosales, H. & Olvera-olvera, C.A. (2020). Comparison of convolutional neural network architectures for classification of tomato plant diseases. *Journal of Applied Sciences*, 12(10): 1–15.

Mohanty, S.P., Hughes, D.P. & Salathé, M. (2016). Using deep learning for image-based plant disease detection. *Frontiers in Plant Science*, 7(4): 1–10.

Noh, S.H. (2021). Performance comparison of CNN models using gradient flow analysis. *Informatics*, 8(3): 1–13.

Santiago, W.E., Leite, N.J., Teruel, B.J., Karkee, M. & Azania, C.A.M. (2019). Evaluation of bag-of-features (BoF) technique for weed management in sugarcane production. *Australian Journal of Crop Science*, 3(2): 1819–1825.

Sijam, K., Ahmad, K. & Seman, Z.A. (2017). Characterisation and pathological variability of *Exserohilum turcicum* responsible for for causing northern corn leaf blight (NCLB) disease in Malaysia. *Malaysian Journal of Microbiology*, 13(3): 41–49.

Thompson, A. & Johnson, A. (1953). A host list of plant diseases of Malaya. *Mycological Papers*, 1(3): 38.

Wang, G., Sun, Y. & Wang, J. (2017). Automatic image-based plant disease severity estimation using deep learning. *Computational Intelligence*, 10(1): 1–9.

Wang, X., Şekercioğlu, Y.A., Drummond, T., Frémont, V., Natalizio, E. & Fantoni, I. (2018). Relative pose based redundancy removal: Collaborative RGB-D data transmission in mobile visual sensor networks. *Sensors*, 18(8): 1–23.

Xie, S., Yu, Z. & Lv, Z. (2021). Multi-disease prediction based on deep learning: A survey. *Computer Modeling in Engineering and Sciences*, 128(2): 439–552.

Yang, B. & Xu, Y. (2021). Applications of deep-learning approaches in horticultural research: a review. *Horticulture Research*, 8(1): 1–31.