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Deep Learning-Based Disease Detection in Sugarcane Leaves: Evaluating EfficientNet Models

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ABSTRACT

Sugarcane is a crucial agricultural crop, providing 75% of the world's sugar production. Like all plant species, any disease that affects sugarcane can significantly impact yield and planning. Traditional manual methods for diagnosing diseases in sugarcane leaves are slow, inefficient, and often lack accuracy. In this study, we present a deep learning-based approach for the robust detection of diseases in sugarcane leaves. Specifically, we trained and evaluated models from the EfficientNetv1 and EfficientNetv2 architectures, which are among the most notable convolutional neural network (CNN) architectures, using the publicly available Sugarcane Leaf Dataset. This dataset includes 11 disease classes and a total of 6,748 images. Additionally, we compared these models with other popular CNN models. Our findings reveal that there is no direct correlation between model complexity, depth, and accuracy for the 11-class sugarcane dataset. Among the 13 models tested, EfficientNet-b6 and InceptionV4 achieved the highest accuracy rates of 93.39% and 93.10%, respectively. These results have a significant impact on how managers can manage diseases and the agricultural processes of sugarcane production. A deep learning-based disease detection system facilitating the diagnostic process can, in turn, result in more accurate and faster identification of diseases. This may enable farmers and agricultural managers to make timely and informed decisions, reducing crop loss and enhancing overall yield. These findings highlight the potential of deep learning in developing fast, accurate, and automatic disease diagnosis systems, which can significantly improve disease management and increase sugarcane yield.

1. Introduction

Agriculture is an important source of income for rural people in developing countries. However, agricultural productivity needs to be increased to meet the food needs of the increasing population [1]. However, the agricultural sector faces various challenges such as plant diseases, pests, and changing weather conditions. Changing weather conditions accelerate the spread of diseases, increasing concerns about food safety.

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The main reason for this study arises from the requirements of better results in sugar agriculture, for instance, the early and more accurate diagnosis of diseases. Since sugar production is of significant financial importance, the on-time and accurate diagnosis of diseases is the key point for the improvement of yield and efficient resource distribution. The traditional techniques are time-consuming and can lead to human mistakes; therefore, the need for the new solutions that can work automatically and give accurate and fast information is inevitable.

Plant diseases pose a serious threat to agricultural production. The sensitivity of agriculture to climate is affected by temperature, precipitation, wind speed and extreme climatic events such as drought, heavy rainfall, hail, and hurricanes. These events can reduce harvests and destroy soil [2]. In particular, the damage caused by plant diseases can be reduced with early diagnosis, but this early diagnosis may be difficult with manual methods. Plant diseases usually start on the lower leaves and spread throughout the crop. Therefore, visual monitoring of leaf diseases in particular rapid detection of diseases and prevention of their spread are critical. Artificial intelligence (AI) and classification methods can help automate this process. AI, especially machine learning and convolutional neural networks (CNNs), can boost precision agriculture by effectively detecting and classifying pests with minimal labor.

In recent years, artificial intelligence techniques have been used to develop expert systems in problem-solving and decision-making. Image processing techniques analyze pixel regions to identify patterns and create algorithms that detect behavioral trends. As a sub-branch of artificial intelligence, deep learning is a feature extraction and classification technique with high adaptability and shows significant potential in agriculture.

Diagnostic methods traditionally based on visual inspections are laborious, costly and relatively less sensitive, and can lead to significant yield losses, especially for rural farmers. Recently, the use of non-invasive methods has attracted attention and allows automatic, fast and accurate solutions [3]. Among these solutions, image processing techniques stand out because they achieve promising results in disease detection and management by utilizing advanced cameras equipped with sensitive sensors. Developments in existing technologies have increased and improved the use of technology in every field [4]. This technological integration promotes sustainability, while automated systems reduce environmental impact by minimizing resource waste. The continuation of these trends leaves autonomous agriculture to play a vital role in meeting global food production needs and addressing challenges such as climate change and resource scarcity [5].

Deep learning algorithms are increasingly used to diagnose and identify diseases in areas such as healthcare and agriculture. The introduction of these technologies in agriculture is an important step towards increasing yields and ensuring food security and sustainability. Advances in deep learning and plant disease diagnosis are particularly important for the sustainability of agriculture. The use of advanced technologies and methods can increase productivity and promote economic growth by enabling early diagnosis of diseases [6,7]. Significant advances in agricultural practices through the use of deep learning models have increasingly increased the importance of research in this area.

2. Related Works

In recent years, significant advances have been made in the fields of deep learning and plant disease diagnosis. The success of CNN and ViT models in natural language processing has drawn attention to this field [8]. Hamuda *et al.* [9] developed an algorithm for automatic product detection, which was used to identify broccoli in video streams under various weather conditions and natural lighting. The identification results were compared with manually labeled ground truth data, achieving an accuracy of 99.04% and a precision of 98.91%. Akbarzadeh *et al.* [10] proposed a method based on support vector machines for plant classification. Experimental findings demonstrated that the proposed algorithm successfully classified plants with an accuracy rate of 97%. Hoang Trong *et al.* [11] introduced a novel approach for weed classification using multimodal deep learning models like Inception-ResNet, MobileNet, NASNet, ResNet, and VGG. They achieved over 98.7% accuracy, enabling real-time weed classification. Structured data extracted from hyperspectral data was used for conducting experiments, where images were employed to identify cotton, sugarcane, and mulberry crops [12]. It was found that deep learning CNN achieved an accuracy of 99.33%, whereas deep FFNN achieved 96.6% accuracy. Hashemi-Beni *et al.* [12] investigated the use of aerial imagery to classify weeds and crops using DL architectures such as U-Net, SegNet, FCNs, and DepLabV3+. Among these, DepLabV3+ achieved the highest accuracy of 84.3%. Veziroglu *et al.* [13] evaluated VGG, ResNet, DenseNet, EfficientNet, Inception, and Xception on the publicly available Paddy Doctor dataset. In the study, the EfficientNetv2_Small model was found to perform better than all models with 98.01% test accuracy and 97.99% F1-score values. Another study used DenseNet, ResNet50 and MobileNet architectures to detect diseases occurring in tomato leaves. The results provided the best performance by the DenseNet model and an accuracy of 0.9900 was achieved [14]. Pacal [15] used 28 CNN models and 36 ViT models on the newly created dataset, combining the PlantVillage, PlantDoc, and CD&S datasets. And achieved accuracy rate of 99.24%. These methods have been recently utilized to visualize lesions on products such as guava [16], tea [17], and apple [18]. Goluguri *et al.* [19] also developed a neural network to predict rice blast disease using meteorological parameters such as wind speed, temperature, rainfall, and relative humidity.

Sugarcane belongs to the Poaceae family has high sucrose sugar and is used in the production of by-products such as white sugar, jaggery (palm sugar), and molasses. 75% of world sugar production is obtained from sugar cane. Thanks to its alkaline structure, sugar cane juice reduces the risk of prostate and breast cancer, supports liver and kidney functions, and regulates blood pressure. However, sugarcane is susceptible to disease outbreaks, which significantly reduces yields [20]. Monitoring plant health is vital for effective planting. Deep learning and image processing techniques can detect diseased leaves, stems, fruits and other affected areas. Many deep learning algorithms are used to distinguish diseased and healthy plants.

Militante & Gerardo [21] evaluated different CNN models for predicting sugarcane disease types using RGB images of sugarcane leaves. The study analyzed three CNN models—LeNet, VGGNet, and StridedNet—on a dataset comprising 7 classes (1 healthy crop and 6 disease classes). StridedNet achieved an accuracy of 90.10%, LeNet achieved 93.65%, and VGGNet achieved the highest accuracy of 95.40%. A simple CNN model used by the study tested a DL model on a large dataset of sugarcane leaves and achieved an accuracy of 95% [22]. The study included three scenarios using various feature extractors: Inception v3, VGG-16, and VGG-19 [23]. The accuracy was evaluated using the receiver operating characteristic (ROC) curve. VGG-16 is used as the feature extractor, achieving an accuracy of 90.2%, with SVM as the classifier. In their study, models achieved a peak accuracy of 93.40% on the test set and 76.40% on images sourced from various reputable online platforms [24]. Two distinct object-detection algorithms, YOLO and Faster R-CNN, were employed and evaluated on our dataset, achieving a top mean average precision score of 58.13% on the test set. The method utilized a CNN trained on approximately 3000 leaf images to function as an image classifier [25]. The model achieved an accuracy of 96%. An Android application is also developed as a user interface for this model. Kai *et al.* [26] developed a methodology to differentiate sugarcane varieties using a dense neural network. The number of hidden layers was determined using the greedy layer-wise method, each containing multiples of four neurons. By comparing the results the SVM model showed the highest precision of 99.55%. Grijalva *et al.* [27] proposed a framework and two models for the automatic

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categorization of aphid infestation on sugarcane leaves using digital imagery and deep-learning CNNs. The models classify images into six levels of sugarcane aphid densities at the leaf level, achieving an accuracy of 86% with Inception v3 and Xception models. Li *et al.* [28] introduced a lightweight hybrid deep learning model designed for fast and accurate detection of sugarcane diseases. Trained initially on the Plant Village Dataset and fine-tuned on a custom dataset with 2095 images of six common sugarcane diseases and healthy sugarcane, this model demonstrated slightly higher accuracy and faster performance compared to other deep learning models. Ribeiro *et al.* [29] tested DarkNet53 for identification with an independent 200 images dataset and obtained 96.6% accuracy compared.

Different researchers have developed methods for the classification of sugarcane disease using image processing techniques to extract the characteristics of plants and recognize the presence of disease [20,30]. The structure of color transformation has been employed to analyze texture in plant leaves and diseases. Arivazhagan *et al.* [31] used Gabor's filter and segmentation on the leaves, and then a network of artificial neurons (ANN) was trained to differentiate between classes. Bashir & Sharma [32] provided a discrete transform algorithm with a specific wavelength was employed to identify the presence of sugarcane diseases, and they used the tree of decision to classify images. The Elementary Learning Machine (ELM) predicted the growth of sugarcane in various areas and had superior performance compared to traditional ANN methods [33].

3. Methodology

In this study, a holistic strategy was followed which included a deep learning approach to the detection of diseases on sugarcane leaves. We utilized the Sugarcane Leaf Dataset, which is openly available. The data augmentation techniques were used for dataset preprocessing which made the model more robust. During the study, we trained and assessed several models of the EfficientNet architecture, which were EfficientNet-b0 through EfficientNet-b7, as well as EfficientNetv2-small, EfficientNetv2-medium, and EfficientNetv2-large. The model also utilized transfer learning which helped in utilizing pre-trained weights to improve model performance. We did the model's performance comparison on accuracy rates challenging by diving into the depth and complexity of the model. The evaluation metrics were the accuracy and other indicators related to the treatment of the data and these were implemented to evaluate the most effective model in the detection of diseases in sugarcane (Figure 1).

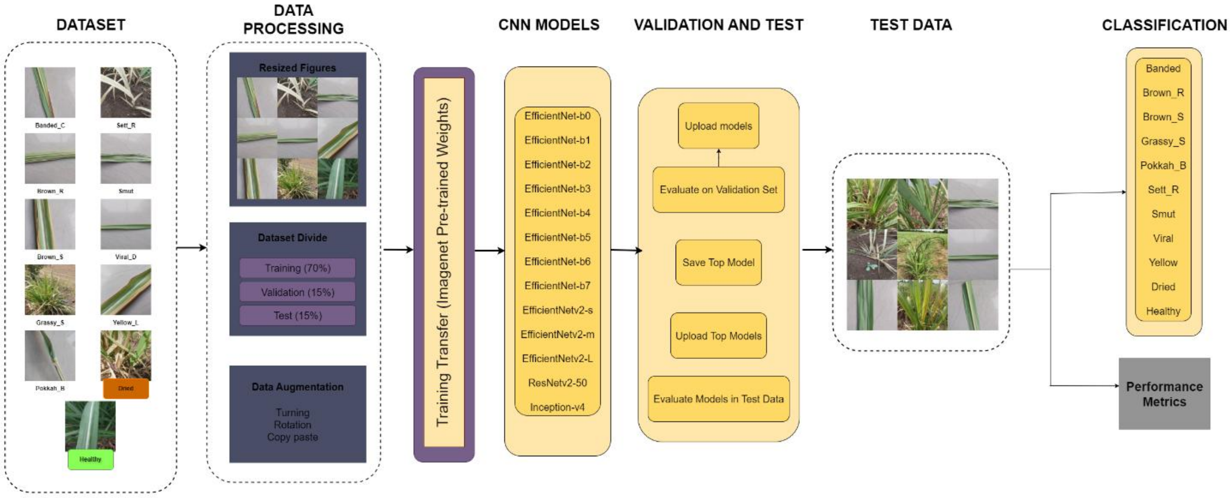

Fig. 1. General approach for classification

3.1 Dataset

Data sets are crucial in both machine learning and deep learning, serving as vital resources that offer rich visual information. These datasets enable researchers, developers, and professionals to train and validate their models, algorithms, and theories effectively. In particular, image datasets focusing on agriculturally specific plants hold significant importance. They provide invaluable tools for researchers and farmers to identify, classify, and study various diseases impacting their crops. Through the analysis of these images, experts can create more precise disease detection algorithms and early warning systems, thereby accelerating disease management and preventing extensive crop damage and yield loss.

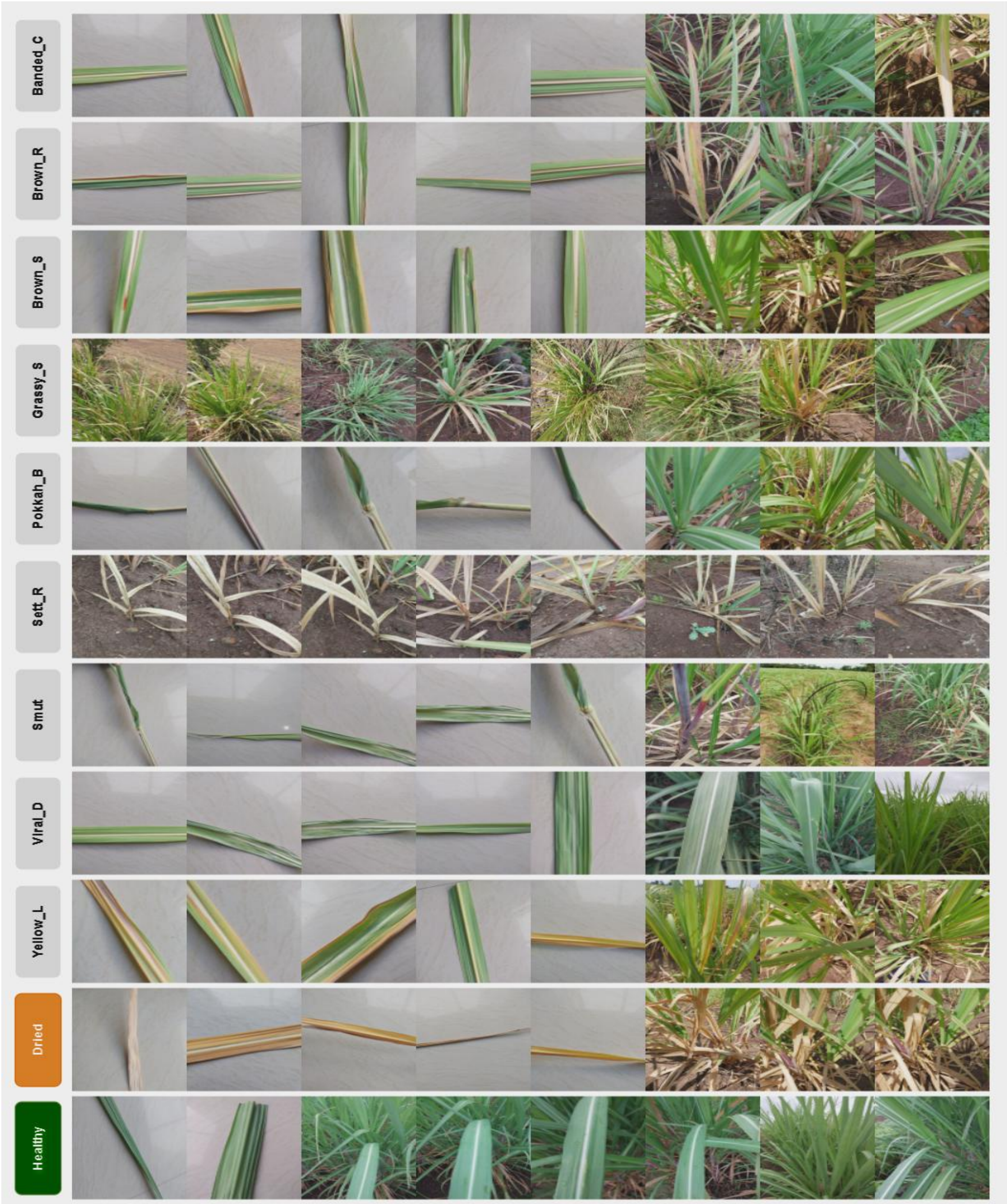

Fig. 2. Examples of leaf images in the sugarcane leaf dataset

The Sugarcane Leaf Dataset consists of 6748 high-resolution sugarcane leaf images. There are 11 categories of diseases in total, dried leaves and healthy leaves [34]. It classifies a variety of common foliar diseases, providing easy access and identification of specific disease examples. Using these images, diseases caused by sugarcane leaves can be detected. In this study, it was aimed to classify diseases using these images. Figure 2 shows examples of leaf classes in the sugarcane leaf dataset. This dataset includes Banded Chlorosis, Brown Rust, Brown Spot, Grassy Shoot, Pokkah boeng, Sett Rot, Smut, Viral Disease, Yellow Leaf diseases, and Dried Leaves, Healthy Leaves plant leaf images.

Table 1
Sugarcane's categories and number of images

Categories	Train(70%)	Validation(15%)	Test(15%)	The Number of Images
Banded Chlorosis	330	71	70	471
Brown Rust	220	47	47	314
Brown Spot	1205	258	259	1722
Grassy Shoot	242	52	52	346
Pokkah boeng	208	45	44	297
Sett Rot	456	98	98	652
Smut	221	47	48	316
Viral Disease	464	99	100	663
Yellow Leaf	836	179	179	1194
Dried Leaves	240	51	52	343
Healthy Leaves	301	64	65	430
Total Number of Images	4723	1011	1014	6748

We encounter Pokkah Boeng disease with at least 297 images, and Brown Spot disease with the most 1722 images. The number of dried leaf images is 343 and the number of healthy leaf images is 430. As in common measurements, the data set is divided into train 70%, validation 15%, and test 15% (Table 1). By dividing it in this way, healthier results were tried to be obtained.

3.2 Transfer Learning

Transfer learning is a technique that aims to shorten training time and increase performance by using the knowledge (weights) of a deep learning model trained for a task on a similar or different problem. Instead of building a new model from scratch for a problem, we can adapt it to the new problem using the knowledge of a pre-trained model. Pre-trained convolutional neural networks such as ResNet and EfficientNet have learned rich feature hierarchies from large and diverse image datasets. This way, we can achieve faster and better results using less data and computational resources.

Especially if you do not have access to large amounts of data, transfer learning offers you the opportunity to obtain better results with less data. It can train the model faster by using the knowledge of a pre-trained model. Transfer learning can enable the model to generalize better to new problems. To apply transfer learning, all weights of the trained model are frozen and only the final layers are fine-tuned for the new problem. In this way, a model trained for more than one task is used and the information of this model is used for the new problem.

3.3 Deep Learning

Deep learning leverages computational models and algorithms composed of multiple layers to analyze data. These techniques can identify intricate patterns in extensive datasets and learn through algorithms, representing the pinnacle of technology advancements in various domains such as speech recognition, image recognition, and object detection. While deep convolutional networks are crucial for tasks like image, video, speech, and audio processing, recurrent networks facilitate the analysis of sequential data, including text and speech [35]. Deep learning architectures have achieved outstanding outcomes in object recognition. They are also utilized in pattern recognition, detection, classification, predictive analytics, drug development, lexicon creation, signal processing, and applications in the medical, financial, and defense sectors. Research indicates that deep learning frameworks yield significantly superior results compared to other established methods [14].

3.4 CNN

CNN, which we commonly encounter in image processing, is a critical artificial neural network model in the field of deep learning. This network model has a special structure consisting of convolutional, pooling and fully connected layers. It works by applying these layers to input data. Convolutional layers create a new matrix that identifies features from the data by looping the filter over the image converted into numerical matrices (Figure 3). Pooling layers preserve these features and reduce the size of the output. These processes repeat, and then, when it reaches the fully connected layer, it uses this processed data in classification or prediction tasks.

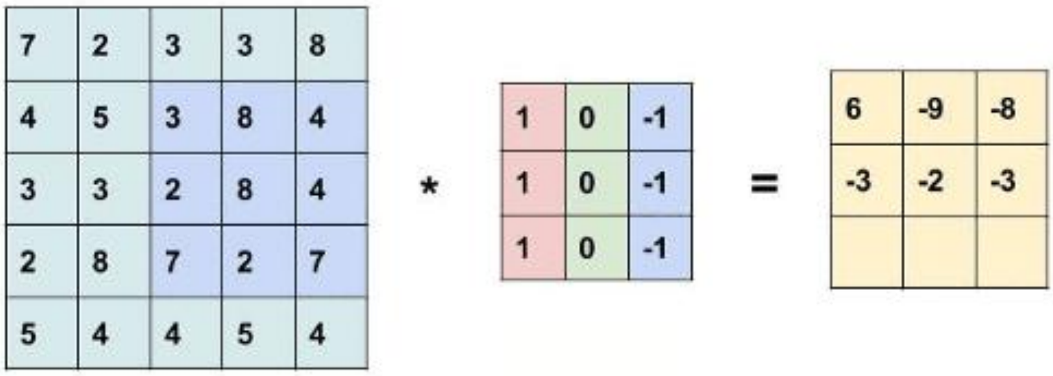

Fig. 3. Feature map extraction in CNN with filter

Training of CNN is carried out by optimizing the parameters by minimizing the error function, which improves the performance of the network. Therefore, CNN stands out as an effective model to achieve high accuracy rates in the fields of image processing and recognition. In structure, CNN consists of a convolutional layer that determines features using filters, an activation function that provides non-linear transformation of convolutional outputs, a pooling layer that preserves features while minimizing the output, and fully connected layers used for classification or prediction (Figure 4). During the training process, the fully connected layers following the convolution, activation and pooling layers perform the learning process by minimizing the error function between the predicted and the real values. This article focuses on EfficientNet models. DenseNet121, ResNet50, InceptionV3 models were included in the study for performance measurement.

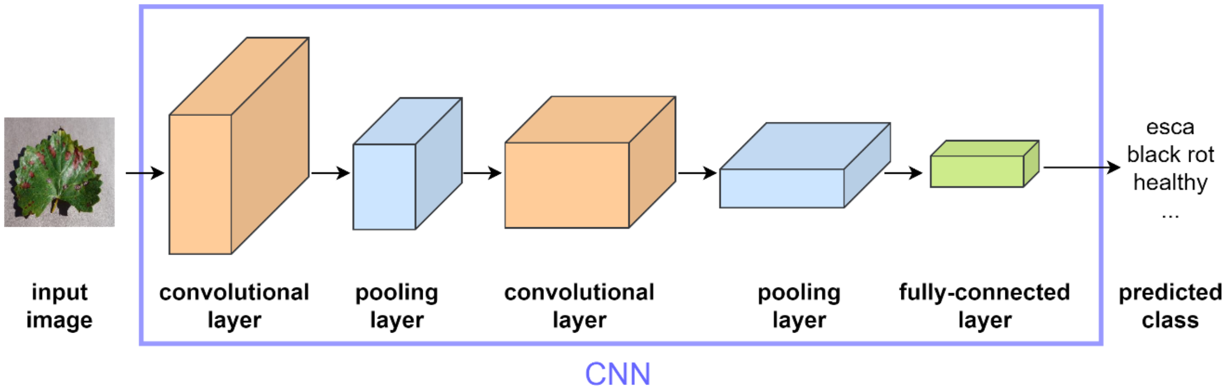

Fig. 4. CNN standard architecture (Kunduracioglu & Pacal, 2024)

ResNet alleviates the vanishing gradient problem encountered when training very deep neural networks [36]. ResNet architecture is a structure that enables deep neural networks with hundreds or even thousands of layers to achieve effective performance by using skip connections between layers. It was proposed to solve the problems of not learning identity maps and corruption and is based on a network architecture consisting of convolution and pooling layers as the building blocks of the network. ResNet uses 3x3 filters like VGG16 and processes input images with a size of 224x224 pixels.

Inception v4, proposed by Szegedy *et al.* [37], is a neural network architecture that aims to reduce computational cost with innovations over previous Inception architectures. Specific techniques employed to reduce computational cost include factorized convolutions, regularization, dimension reduction, and parallel computations. Developed by Google, Inception v3 is the third release in the Deep Learning Evolutionary Architectures series. After the development of Inception V1 and the application of batch normalization in Inception V2, the idea of factorization was introduced in Inception v3. The primary goal of factorization is to reduce the number of connections and parameters without reducing the efficiency of the network. The model itself consists of symmetric and asymmetric building blocks containing convolutions, average pooling, max pooling, concats, dropouts, and fully connected layers. Inception V4 was fine-tuned using pre-trained weights from ImageNet. A new model was also created and defined with an average pooling layer (8x8), dropout and softmax in the upper layer.

3.5 EfficientNet

EfficientNet is a convolutional neural network architecture and scaling technique that scales depth, width, and resolution dimensions evenly using a compound coefficient [38]. The EfficientNet family is built upon an optimized base architecture and an effective scaling strategy. More than a million photos from the ImageNet database are used to train EfficientNet-b0.

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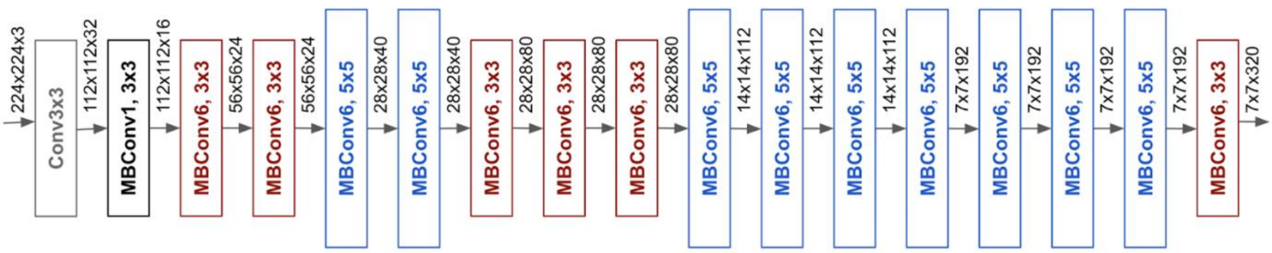

Fig. 5. EfficientNet-b0 architecture [38]

Typically, image classification accuracy is increased by feeding the network with higher resolution images that contain more and finer details, widening the network by adding more filters to each layer, and deepening an already-existing network by adding more layers through which data is passed (Figure 5). EfficientNets increases accuracy by scaling these three components together and designing a ratio that prevents any of them from becoming a bottleneck. By scaling EfficientNet-b0 in this way, the EfficientNet-b4 network with approximately four times more processing power is produced [38].

4. Results

It compares performance metrics for Resnetv2-50 and Inception-V4 models as well as EfficientNet models (Table 2). When the given metrics are examined, the EfficientNet-b6 model shows the highest performance in terms of all metrics. However, it requires more computational resources due to the high number of parameters. The Inception-v4 model is notable because it provides high accuracy and good balance. The EfficientNet-b0 model offers a good accuracy rate with few parameters, indicating that it may be suitable for situations with limited computational resources.

Table 2
The performance measures of classification by EfficientNet and other models

Model	Params	Acc	Precision	Recall	F1-score
EfficientNet-b0	4.01m	0.9260	0.8953	0.8942	0.8911
EfficientNet-b1	6.53m	0.9132	0.8776	0.8712	0.8712
EfficientNet-b2	7.72m	0.9280	0.8972	0.9010	0.8984
EfficientNet-b3	10.71m	0.9290	0.9000	0.8948	0.8933
EfficientNet-b4	17.57m	0.9290	0.9031	0.8986	0.8931
EfficientNet-b5	28.36m	0.9053	0.8764	0.8571	0.8640
EfficientNet-b6	40.76m	0.9339	0.9258	0.9071	0.9094
EfficientNet-b7	63.82m	0.9280	0.8995	0.9023	0.8956
EfficientNetv2-small	20.19m	0.9300	0.9068	0.9081	0.9036
EfficientNetv2-medium	52.87m	0.9211	0.8900	0.8900	0.8868
EfficientNetv2-large	117.25m	0.9014	0.8876	0.8882	0.8822
ResNetv2-50	23.52m	0.9260	0.9887	0.8907	0.8916
Inception-v4	41.16m	0.9310	0.9123	0.8920	0.8940

If we look at what the given metrics mean; parameters indicate the total number of parameters of the model and determine the complexity and computational requirements of the model. EfficientNet-b0 has the fewest parameters (4.01m) while EfficientNetv2-large has the most parameters (117.25m). Increasing the number of parameters generally increases the computational cost and memory requirements of the model. Accuracy refers to the proportion of samples that the model predicts correctly overall. The EfficientNet-b6 (0.9339) and Inception-v4 (0.9310) models have the highest accuracy rate. This shows that these models perform quite well on the dataset. On the other hand, EfficientNetv2-large has the lowest accuracy rate (0.9014), indicating that the model is less successful than others. Precision measures the accuracy of the model's positive predictions and is high when false positives are few. The highest precision is seen in the ResNetv2-50 model with 0.9887. This shows that the model minimizes false positives. EfficientNet-b5, on the other hand, has the lowest precision (0.8764), indicating that the model makes more errors in its positive predictions. Sensitivity refers to the rate at which the model correctly predicts true positives and is high when false negatives are few. EfficientNet-b6 has the highest sensitivity with 0.9071 recall, indicating that the model successfully detects true positives. EfficientNet-b5, on the other hand, has the lowest sensitivity with 0.8571 recall, which means the model misses some positives. The F1-score measures the balance between precision and sensitivity and is the harmonic mean of the two. The highest F1-score is seen in the EfficientNet-b6 (0.9094) model. This indicates that the overall performance of the model is quite stable. EfficientNet-b5 has the lowest F1 score (0.8640), indicating that the model is less balanced between precision and sensitivity.

This analysis can help select the most appropriate model depending on a particular use case. While models such as EfficientNet-b6 are preferred for situations requiring higher accuracy and F1 score, lighter models such as EfficientNet-b0 can be preferred in cases where computational resources are limited. In addition, although the accuracy rate is expected to increase as model complexity increases, it has been determined that there is no such relationship between the models. This shows that complexity is not directly proportional to accuracy. However, it is thought that this result was reached due to the small size of the data set. Different results may be obtained in larger data sets.

Confusion matrix is a table of metrics used to evaluate the performance of the classification model. This matrix shows the relationship between the actual classes and the classes predicted by the model. Often used in classification problems, the confusion matrix forms the basis for calculating the model's accuracy, sensitivity, specificity, and performance metrics such as recall and F1-score.

The number of true positives is the number of positive examples that the model predicted correctly. The number of true negatives is the number of negative examples that the model predicted correctly. The number of false positives is the number of samples that the model predicted as positive but were actually negative. The number of false negatives is the number of examples that the model predicted as negative but were actually positive. These four values indicate how correctly or incorrectly the model predicted each class. Confusion matrix is crucial to understanding the performance of the model and is used in developing and tuning classification models. As seen in Figure 6, EfficientNetV2-S and InceptionV4 have high TP rates and low FP and FN errors. However, ResNetV2-50 and EfficientNet-B6 make more FP and FN errors. Differences were seen between classes; some classes (e.g. Smut) are generally predicted with low accuracy across all models, while others (e.g. Grassy_S) are predicted with high accuracy across all models. Each model has its strengths and weaknesses; which model to use may depend on the performance on a particular class or feature set.

Table 3 evaluates the performance of the EfficientNet_b6 model for the identification of sugarcane diseases and healthy plants according to the classes in the dataset. The report measures the performance of the model on different classes with accuracy, sensitivity, F1 score and number of images used for each class. These metrics are used to understand how well the model identifies certain classes.

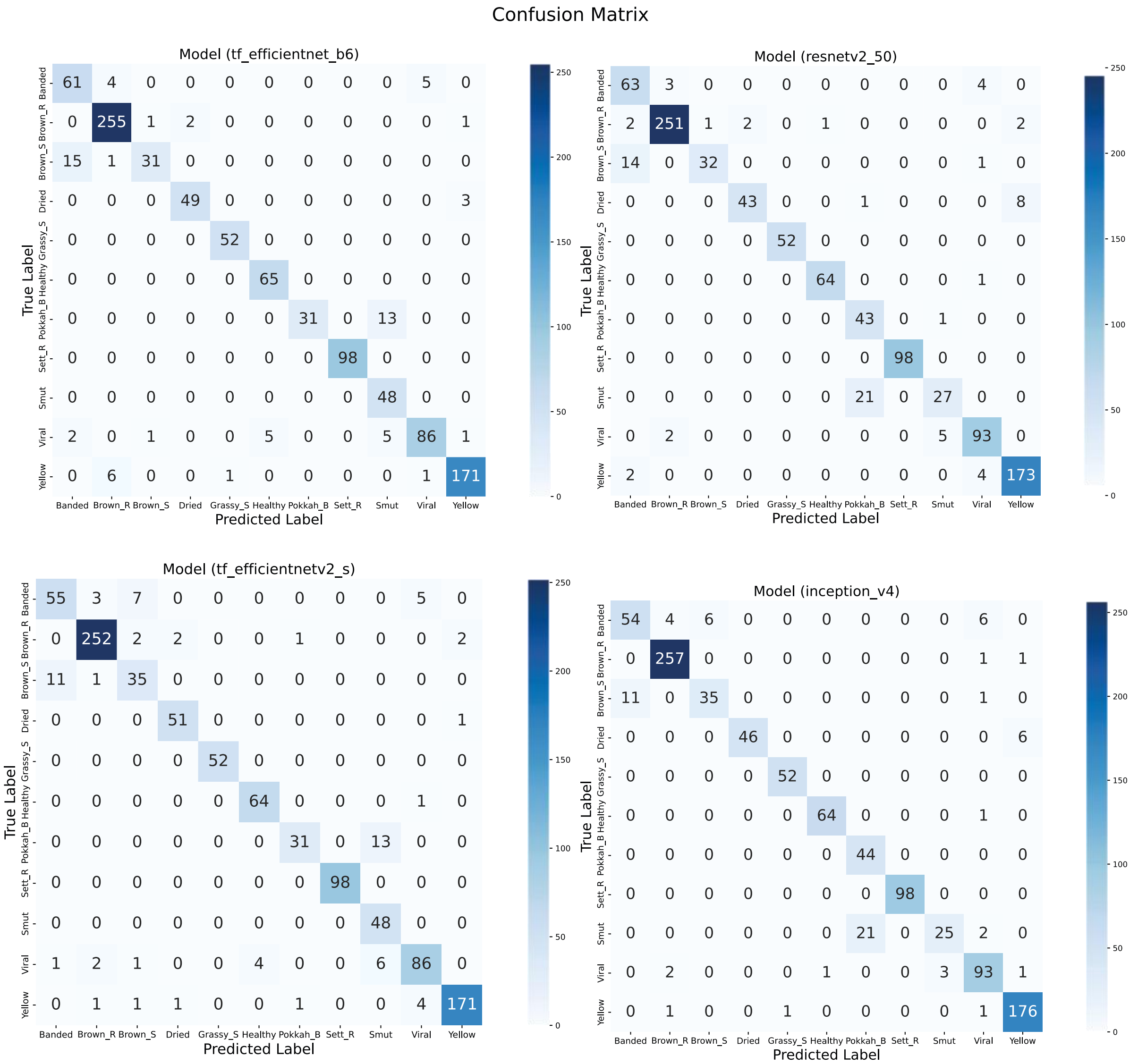

Fig. 6. Confusion matrices for some models

Although the accuracy of the model is relatively low for Banded, the sensitivity is high. These results indicate that the model accurately identifies this class, but its overall performance is slightly lower. In the Brown_R class, the model exhibits a very high performance. Accuracy, sensitivity, and F1-score are very high, indicating that the model correctly identifies this class. Although the accuracy of the model is high in the Brown_S class, the sensitivity is quite low. This indicates that the model had difficulty recognizing this class and missed some positive examples. In the Grassy_R class, the model shows near-perfect performance. Sensitivity and F1-score are very high, indicating that the model correctly identifies all positive examples. Although the accuracy of the model is high in the Pokkah_B class, the sensitivity is low. This means that the model missed some positive examples. In the Sett_R class, the model shows excellent performance. All metrics are 1.00 (Table 3), indicating that the model completely and accurately describes this class. In the Smut class, the sensitivity of the model is very high, which indicates that the model correctly identifies all positive examples. However, the accuracy is lower, which indicates that the model produces some false positives. The model's accuracy and F1 score are high in the viral class. Although the sensitivity is relatively high, it misses some positive examples. The model in the Yellow class shows very high performance. Accuracy, sensitivity, and F1-score are high, indicating that the model correctly identifies this class. The performance of the model is very good in the Dried class. Both accuracy and F1 score are high, indicating that the model correctly identifies this class. In the Healthy class, the sensitivity of the model is very high, which indicates that the model correctly identifies all healthy plants. Accuracy and F1-score are also quite high.

Table 3
Classification Report

Class	Acc	Recall	F1-score	Number of images
Banded	0.7821	0.8714	0.8243	70
Brown_R	0.9586	0.9846	0.9714	47
Brown_S	0.9394	0.6596	0.7750	259
Grassy_S	0.9811	1.00	0.9905	52
Pokkah_B	1.00	0.7045	0.8267	44
Sett_R	1.00	1.00	1.00	98
Smut	0.7273	1.00	0.8421	48
Viral	0.9348	0.8600	0.8958	100
Yellow	0.9716	0.9553	0.9634	179
Dried	0.9608	0.9423	0.9515	52
Healthy	0.9286	1.00	0.9630	65

This report reveals that the model generally performs well on most classes, but requires improvement on some classes (particularly Pokkah_B and Brown_S). The model performs excellently in Sett_R and Grassy_R but has lower accuracy rates in classes such as Smut and Banded. This analysis is useful to identify the strengths and weaknesses of the model and make improvements where necessary.

5. **Discussion**

Among the many studies that have been done, this one stands out as being unique and different from all the others by doing a thorough and comprehensive evaluation and comparison of various model of the EfficientNet architecture. The research entails conducting a rather exhaustive comparison of the performance of the varied EfficientNet architectures, that is, starting from the smallest – “b0” through the largest – “b7” families as well as the EfficientNetV2 families which would consist of EfficientNetV2-small, EfficientNetV2-medium, and EfficientNetV2-large.In this case, one can gain insight into the accuracy of the models under different depths, thereby analyzing their structures. Unlike the traditional methods, deeper study of the learning approach reveals that incorporating automated deep learning provides more powerful and effective results. This research, thus, insinuates that deep learning can achieve both high accuracy and speed in identifying sugarcane diseases, hence the advantages offered to disease diagnosis by this approach. Artificial intelligence-driven applications overcome the obstacles and deliver unfathomable speed and precision in diagnosing patients, thus maximizing resource utilization and boosting overall efficiency. In addition to the decrease in the dependence on labor and the cost cutting on large-scale farming that the automatic systems lead, there are significant pluses. Thus, the comparison of different achievable versions of EfficientNet models definitely becomes a means of finding out what the strengths and weaknesses of each model are. As a result, the most suitable model is going to be selected.

6.Conclusion

Deep learning methods have recently become popular for image processing. In this study, the classification of sugarcane leaf images belonging to 11 classes of the Sugarcane Leaf Dataset was investigated. For this purpose, EfficientNet models were examined and the basic models ResNetv2-50 and InceptionV4 models were compared. Highest accuracy rates were found by EfficientNet-b6 (0.9339) and Inception-v4 (0.9310) models. Models with low accuracy such as EfficientNet-b5 (0.9053) and EfficientNetv2-Large (0.9014) still achieved high accuracy. However, the fact that EfficientNetv2-large (117.25m) has the lowest accuracy, as the model with the highest model complexity, shows that when the model complexity and accuracy rate are compared, no significant relationship can be found. When making this comment, it is necessary to consider that a small-scale data set is used. This may cause different results in real applications. For this reason, renewing the study with large data sets in future studies will increase the accuracy and validity compared to real data. For this reason, models such as EfficientNet-b6 are preferred where high accuracy and F1-score are important, while low complexity models such as EfficientNet-b0 can be preferred in cases of limited resources. Since more realistic results can be obtained with larger data sets, the data set can be enlarged in future studies. Also in future work, we would like to validate the proposed model in a live deployment.

Author Contributions

Conceptualization, İ.K.; methodology, İ.K and İ.P.; software, İ.P.; validation, İ.K and İ.P.; investigation, İ.K. and İ.P.; resources, İ.K.; writing—original draft preparation, İ.K.; writing—review and editing, İ.K. and İ.P.; visualization, İ.K.; supervision, İ.P. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

We used a public dataset which Sugarcane Leaf Image Dataset. For access https://data.mendeley.com/datasets/9twjtv92vk/1

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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