Leveraging EfficientNetB4 Model with Multi-head Attentions for Maize Leaf Disease Detection

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Abstract. Smart agriculture mainly stresses the improvements in early plant disease diagnostics, crop classification and management, and effective pest control. Maize being an important staple crop necessitates early and accurate disease detection on its leaves. Hence, this paper proposes a novel Convolutional neural network model based on EfficientNet-B4 model and multi-head attention for the effective classification of maize leaf diseases. The proposed model focuses on early-stage disease patterns with the help of a large amount of data. Compared to other architectures, it attains an outstanding F1-score of 96.75%. The proposed system not only helps farmers to get timely diagnosis but also offers them useful information to mitigate risks and improve production. This study benefits agricultural resilience, food security and farmer's welfare.

Keywords: Maize leaf · disease · attention · smart agriculture

1 Introduction

Maize crop is an important staple meal for millions of people in the world, and it is an important ingredient crop for several food industries like meat and milk production, energy production, chemicals and products produced from animal and plant waste, and medicine. Hence, maize crop diseases, pest infestation of the maize, and nutrient deficiencies also need to be managed in an efficient manner to ensure that the maize crop remains healthy and productive. Diseases caused to the leaves of maize cause a serious threat to the quality and production of maize and cause huge financial losses to farmers. Therefore, to implement control measures for maize disease control, it is crucial to be able to quickly identify the particular type of disease so that precision medication can be provided.

Today's disease identification is a slow, time-consuming, and highly subjective process that involves farmers' observations. The objectives of this study are to design an efficient deep learning model to diagnose diseases in maize leaves.

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The proposed model specifically targets at identifying diseases like grey leaf spot, maize rust and northern blight through more complex convolutional neural networks since the task is primarily an image analysis task. The objective is to design a basic gadget that can be used by farmers and agronomists to diagnose diseases in the leaves of the maize crop early and in the process, be able to come up with sustainable measures to control the diseases.

It contributes to the field of smart and precision agriculture and its key contributions include:

- A novel approach fine-tuning EfficientNetB4 convolutional neural network by integrating multi-head attention mechanism optimally into the architecture.
- Analysis on the impact of multi-head attention mechanism added at different positions in the model architecture to find the most optimal architecture for disease classification.
- Analysis and implementation of five recent state-of-art convolutional neural networks for model selection and comparative performance analysis against the proposed model.

2 Literature Survey

Nowadays, there has been a lot of focus on smart agriculture, thereby, making several researchers focus on the development of automated systems for crop monitoring, disease detection, classification etc. This section discusses some of the notable works proposed to date for the detection and classification of different crop leaf diseases. Sun et al. [1] proposed a system for crop disease identification utilizing convolutional neural networks with multiplexed feature aggregation technique, Retinex enhancement, and huge RPN having a transmission module for enhanced localization accuracy. Their method shows a significant improvement in the degree of precision and perceptible FPS rates compared to earlier strategies.

Haque et al. [2] used deep learning for diagnosing diseases from field images in Ludhiana India by using synthetic photos with turning and light enhancement. To build a model for detecting watermelon diseases, they trained Inception-v3, and the results were good regardless of background settings. In the current study, Masood et al. [3] introduced MaizeNet, a deep learning model that integrates spatial channel attention and an improved Faster R-CNN for the identification of maize leaf diseases. This model showed that the system was stable in different climatic conditions and provided an answer to the problem of ecosystem productivity. Qian et al. [4] proposed a transformer-based model for the detection of Maize leaf diseases, reducing background distortion through self-attention and multi-source image datasets.

Rai et al. [5] reviewed NLB, a fungal disease that hazards maize. Several state-of-art models were trained from scratch with data augmentation techniques and Adam optimizers up to 50 epochs and the results were excellent. The attention U-Net proved to be better than other segmentation approaches, thus allowing accurate NLB disease segmentation using local features. Yin et al. [6] proposed DISE-Net for identifying the maize leaf spot disease that improves the feature transmission, cross-channel coupling, and multi-scale feature learning as a deeper network with better accuracy than InceptionV3, ResNet50, and VGG16. Grad-Cam visualization affirms its main area of interest, which is a handy tool for field classification. Waheed et al. [7], classified corn leaf disease using the DenseNet model, beating highly parameterized models such as EfficiencyNet and VGG19Net models while having a slight difference in classification accuracy, meaning that it consumes less computation resources.

Craze et al. [8] applied deep learning to maize leaf diseases' classification and specifically on GLD. Classifiers were trained on combined cornfield photos with diseases and it was noted that models from actual images are more generalized than simulated ones. In another research by Yu et al. [9], they integrated K-means clustering with highly advanced deep learning models to improve a precise maize disease diagnosis particularly the leaf spot, grey spot, and rust diseases with the help of models such as Inception v3, ResNet18, VGG-16, and VGG-19. Sibiya et al. [10] developed a CNN network for the estimation of maize common rust disease severity. The authors apply threshold segmentation with respect to the damaged leaf area and apply fuzzy decision rules to classify it with four severity classes. This AI-based operation introduces new interesting means for plant pathology assessment.

Deep Forest was used by Arora et al. [11] for classification of corn leaf diseases and the results demonstrated a higher accuracy and less time consumption than the traditional machine learning and artificial neural networks. The Deep Forest model almost achieved near to perfect accuracy with very little changes in hyperparameters which makes it suitable for maize leaf classification. To overcome the issue of delayed disease identification, Pan et al. [12] developed a deep learning method for white corn health diagnosis with more images for better decision and disease diagnosis. Pushpa et al. [13] worked on disease identification for early intervention for sustainable crop production with 92% accuracy after using train and test split.

Veni et al. [14] put forward a deep learning approach to mitigate the crop yield reduction by plant diseases. They employed the deep learning models in the classification of plant leaf diseases employing the support vector machines and k-nearest neighbour. Satvika et al. [15] used RGB to HSI conversion, k-means clustering, GLCM and SVM classifiers for crop disease recognition and the accuracy achieved was 93.5%. Indeed, Vijayakumar et al. [16] were engaged in the rice plant disease identification by using image processing techniques such as CNN, CNN with the data augmentation, and GAN to enhance the crop productivity through the early sign identification of a disease for appropriate fertilization.

Several other image classification techniques have been proposed to date in various computer vision applications like remote sensing, medical imaging, crop classification, disease predictions, etc. These techniques can be studied by referring to [17–21].

Haq et al. [23] developed an automated weed detection system based on a CNN LVQ model on 4400 UAV images with 100% accuracy of soil, 99.79% of soybean, and overall accuracy of 99.44%. The weed detection performance of the model was higher than previous studies after hyperparameter optimization. Haq et al. [24] proposed a five-layered CNN model for plant image identification with 300 images of nine plants. The model yielded a 96% accuracy on the NU108 and 97.8% on UAV images of the NU101 dataset, which proves the efficiency of the model in plant classification.

Haq et al. [25] employed high-resolution PlanetScope (PS) nanosatellite data to analyze temporal and spatial dynamics of agricultural land in the Al-Qassim region of Saudi Arabia. Compared with NDVI and Multinomial Logistic Regression (MLR), the Random Forest (RF) model yielded 98% accuracy in vegetation classes, which proved the model's ability to model complex variables and filter noise.

3 Dataset Details and Processing

For the purpose of this work, A standard Maize leaf dataset has been used. The dataset contains 4000 images of maize leaf diseases belonging to four different categories namely, Bercak Daun, Daun Sehat, Hawar Sehat and Karat Sehat. All the images in the dataset have been resized to a consistent image size of 200×200 pixels. Several image augmentation techniques have also been applied to increase the diversity of the dataset images. The applied transformations are the zoom_range with a value of 0.15, width_shift_range with a value of 0.2 and shear_range with a value of 0.15. This augmented dataset is used for the model training and testing purposes. For comprehensive model training, stability and testing, the dataset has been divided into three different sets namely, the train set, validation set and test set in the standard ratio of 60:20:20 with 600 images for each class in training and 200 images for each class in validation and test dataset.

4 Proposed Methodology

The methodology proposed in this paper exploits the efficiency of the recent EfficientNetB4 model and multi-head attention mechanism for automatically detecting and classifying diseases in the Maize crop leaf. Instead of blindly selecting the EfficientNetB4 model as the baseline model for the proposed approach, the work experiments with fine-tuning of five recent state-of-art and efficient convolutional neural networks for Maize leaf disease detection namely, DenseNet201, InceptionNetV3, MobileNetV3, XceptionNet and EfficientNetB4. All the models pre-trained on ImageNet dataset are selected and their weights are extracted as it is. The top layer of the models is removed and an additional Global average pooling layer is added followed by three additional dense layers having 1024, 1024 and 512 neurons with ReLU activation function. Finally, the last layer is added with 4 neurons and Softmax activation function. Here, the performance of EfficientNetB4 model surpasses all the models.

EfficientNetB4 convolutional neural network is a deep, wide, and high-resolution in architecture. This model uses compound scaling that balances depth, width and resolution rather than just depth scaling. It is designed to ensure better performance and efficiency by optimising layer width, depth and resolution. It contains the blocks which perform the implementation of the depth-wise separable convolutions with squeeze and excitation blocks, including the usage of batch normalisation and Swish activation functions.

Here, depthwise separable convolutions are substantially instrumental in reducing the number of parameters and computation for efficiency while Squeeze-and-excitation blocks further refine feature representations by explicitly modeling channel-wise dependencies. It also uses Global average pooling layers that reduce spatial dimensions, enabling generalization without over-fitting. It should be noted that the Swish function is recently favoured frequently due to its great performance. The model is advanced and performs better due to the increased scaling factors in higher ratings. Such meticulous design achieves state-of-the-art results for every image classification task, clearly demonstrating the fact that EfficientNetB4's architectural principles are functional in attaining high performance but with improved efficiency.

The rationale for selecting EfficientNetB4 over higher counterparts including EfficientNetB5, EfficientNetB6, or EfficientNetB7 was as follows. Although the higher variants provide higher scaling factors and potentially higher performance, they need much more GPU memory, higher computational capability and longer training time. Training or inferring with models like B5, B6, or B7 would have imposed actual limitations for computational hardware and exorbitant computational cost would ensue.

Based on these factors, the EfficientNetB4 model is a perfect middle ground between high performant model and a model with reasonable computational requirements. It provides very good performance for the maize leaf disease detection task and has reasonable resource consumption which is quite appropriate given the hardware and time limitations.

Multi-head attention, on the other hand, includes an inventory mechanism of different heads which, in transformer-based architectures, serve the purpose of capturing all the disparities that can exist in sequence inputs. Every day new attention head finds its own multi-level attention signatures by independently making attention scores for projected query, key, and value vectors. These scores are for the sake of computing weighted sums of values vector from multi-head attention output vector for the specific position in the sequence. Through simultaneously taking into account different representations of information from multiple subspaces, this kind of attention enables the model to efficiently learn how to understand and process the complex sequences which, in turn, results in improved accuracy of tasks.

The design of the multi-head attention is controlled by two key components (a) num_heads and (b) key_dim. *num_heads* in the multi-head attention mechanism specifies the number of parallel attention heads to be employed. Multiple attention heads enable the model in capturing and analyzing a variety of patterns and relationships in different regions of the input data images parallelly at the same time. Adjusting this parameter impacts model's process of learning and analyzing information from several different perspectives. The higher the value of num_heads, the more aspects of the input the model can attend to at the same time, possibly improving the performance, at the cost of higher computational complexity. The proposed model employs a total of eight attention heads. While the *key_dim* represents the projected key's dimensionality and value vectors' dimensions in each attention head. With the help of this parameter, it is able to decide the granularity of captured information in each attention head which increases the model's ability to understand relationships between tokens. The key_dim parameter should be large enough to capture meaningful information but small enough to make the computation efficient. Typical values for key_dim are between 64 and 512, but the best choice depends on the complexity of the task and the resources available. The proposed model employs a key_dim of value 64 only.

4.1 Integration of EfficientNetB4 Model and Multi-head Attention

Before the proposed solution – combination of the EfficientNetB4 CNN model with the Multi-head Attention (MHA) mechanism – the EfficientNetB4 model, pretrained on the ImageNet database, is further trained on the Maize leaf database. This is done by stacking a global pooling layer and a few dense layers way at the end of the model. The EfficientNetB4 model is loaded and the final classification layer is stripped off from the model. A GAP layer is then included to down sample spatial dimensions and three dense layers with 1024, 1024, and 512 neurons respectively. These layers employ rectifying linear unit nonlinearity function to make the computations faster. The final output dense layer comprised of 4 neurons to make multi-class predictions with the Softmax activation across the four diseases. The final layer employs categorical cross entropy for measuring the error for back propagation while the performance measure here is accuracy. EfficientNetB4 model is utilised with pre-trained weights at the base instance.

Once the architecture is optimized and the disease classification results are reasonable, the proposed methodology adds multi-head attention (MHA) layers at different positions between the dense layers. The different configurations tested are: We also compare the following architectures: (a) one MHA layer after the first dense layer (DL-1), (b) one MHA layer after the second dense layer (DL-2), and (c) two MHA layers after both DL-1 and DL-2. These multiple layers in the MHA means that the model can attend to a different part of the input sequence, the relationships within the data can be captured with more efficacy. These configurations were tested to determine an architecture that enhances the model's performance without adding more parameters or computational complexity.

The first two architectures enhanced the fine-tuned EfficientNetB4 model by a slightly better accuracy of classification of maize leaf diseases, while the three dense layers and two attention layers provided the best results. This combination enables the model to capture more complex features and relations in the data and thus perform better in the multi-class classification problem. The complete architecture can be seen in Fig. 1 below. EfficientNetB4 with multi-head attention layers is used to capture long-range dependencies in image data to capture dependencies that are important in complex pattern recognition tasks.

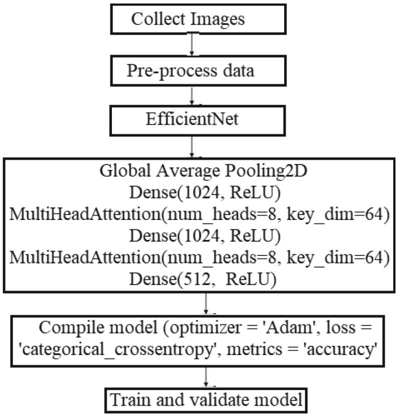

Fig. 1. Proposed system architecture for fine-tuned EfficientNetB4 model integrated with multi-head attention mechanism

5 Experiments

A common set of hyper-parameters is adopted for learning of all the deep learning models like DenseNet201, InceptionV3, etc., implemented for this work. Images are resized to 224×224 pixels and processed in batches of 32 for faster model training and error back-propagation. All the hidden layers employed ReLU activation function for faster computations while facilitating the multi-class classification, final output layer Softmax activation function. The Adam optimizer adjusts model parameters for optimal model learning by minimizing the categorical cross-entropy loss function over 30 epochs with a learning rate of 0.0001 (Table 1).

All the models have been comprehensively evaluated using Recall, Precision, Accuracy and F-score metrics (Fig. 2). Among the evaluated combinations of dense layers and multi-head attention layers, the proposed fine-tuned EfficientNetB4 model with three dense layers and two multi-head attention layers after DL-1 and DL-2 demonstrates the highest performance with an accuracy of 96.63% and the best F-score of 96.75% on the test set, indicating its effectiveness in making correct predictions. Following closely, EfficientNet (Layer 1) achieves an accuracy of 95.63%, while EfficientNet performs at 95.63%, EfficientNet (Layer 2) at 95.12%. Accuracy and F-score are the key metrics for

Table 1. Experiments of Fine-tuned EfficientNetB4 model with different combinations dense layers (DLs) and Multi-head attention (MHA) layers

Models	Precision	Recall	F1	Accuracy
3 DLs only	0.9575	0.9550	0.9575	0.9562
3 DLs + 1 MHA layer after DL-1	0.9575	0.9575	0.955 0	0.9563
3 DLs + 1 MHA layer after DL-2	0.9550	0.9500	0.9500	0.9513
3 DLs + 2 MHA layers after DL-1 DL-2	**0.9650**	**0.9625**	**0.9675**	**0.9663**

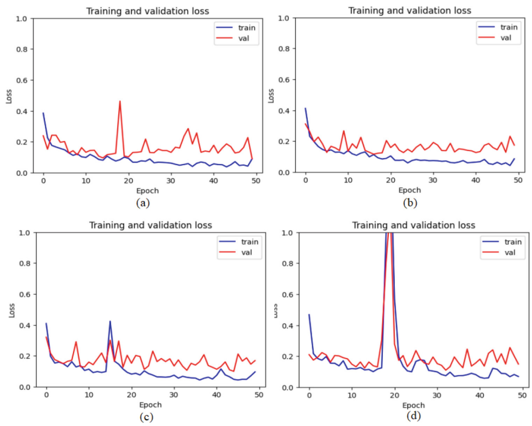

Fig. 2. Learning plots obtained for different combinations of Dense layers and multi-head attention layers applied for fine-tuning of EfficientNet-B4 model (a) without MHA layer,(b) with MHA layer after DL-1, (c) with MHA layer after DL-2 and (d) with MHA layers after DL-1 and DL-2

classification tasks, representing the percentage of correct predictions. However, the selection of the best model may also hinge on other considerations such as computational efficiency, interpretability, and alignment with specific task requirements. In this context, if the model is required to be kept lighter and to be installed on edge devices, one can opt for the EfficientNetB4 model fine-tuned with dense layers only.

The stability in the learning of different architecture of fine-tuned EfficientNetB4 model can be studied by referring to Fig. 1. The loss plots for all these different combinations over 50 epochs show a clear model convergence without over-fitting or under-fitting on the Maize leaf dataset images. It can be observed that during initial epochs, the models had huge fluctuations for both training and validation loss values but slowly towards the 50th epoch, the models converged properly with a stable learning process.

Amongst the different combinations of fine-tuned EfficientNetB4 model trained on the test set, fine-tuned EfficientNetB4 model with 3 dense layers only has the lowest test loss of 0.1404. While other combinations EfficientNetB4 with 3 dense layers and 2 multi-head attention layers had a loss of 0.1404, EfficientNetB4 with 3 dense layers and 1 multi-head attention layer after the first dense layer had a loss of 0.146 and EfficientNetB4 model with 3 dense layers and 1 multi-head attention layer after the second dense layer had a loss of 0.1794 which are relatively higher test losses. Lower loss values indicate that the model is better at minimizing the difference between its predictions and the actual target values. While loss is a crucial metric, the choice of the best model strongly depends on other metrics as well like F-score and accuracy which were the highest for the proposed model.

Table 2. Performance comparisons of proposed model against state-of-art models.

Models	Precision	Recall	F-score	Accuracy
MobileNetV2	0.84	0.8225	0.83	0.8312
DenseNet201	0.935	0.925	0.9275	0.9262
XceptionNet	0.87	0.87	0.8725	0.87
InceptionNetV3	0.86	0.8525	0.8575	0.8537
EfficientNetB4	0.9575	0.955	0.9575	0.9562
Proposed model	**0.9650**	**0.9625**	**0.9675**	**0.9663**

Table 2 compares several state-of-art deep learning models for Maize leaf disease classification tasks, with EfficientNetB4 model emerging as the best baseline performer model. DenseNet201 model also performed decently in identifying the leaf disease while MobileNetv2, XceptionNet, and InceptionNetV3 model had very low F-score and accuracy values in detecting the leaf disease. The efficientNetB4 model achieves the highest scores in Precision (0.9575), Recall (0.955), F1 Score (0.9575), and Accuracy (0.9562). This indicates that EfficientNetB4 excels in accurately identifying true positives while minimizing false positives to its maximum, making it the most effective model overall with a minimum of 3% improvement in all the metrics over all other state-of-art baseline methods. This made the EfficientNetB4 model our natural choice to further leverage the classification accuracies for the underlying Maize leaf disease detection task.

Finally, as discussed above, further leveraging the fine-tune EfficientNetB4 model with two additional multi-head attention layers increased the efficiency of the model in correctly detecting and classifying the disease type of Maize crop leaf with the highest F-score of 97% approximately. The multi-head attention layers proved to improve the alignment of the model on the parts of data which aided in focussing on the relatively important image regions to extract more informative features, thereby, increasing the model's efficiency.

Next, Fig. 3 presents the loss plots for the baseline models implemented. It can be seen that all the models learnt well and showed learning saturation within 50 epochs. The major difference to be noted here is that for MobileNetV2 model's validation loss kept fluctuating between a fixed range of 0.4 to 0.7 which

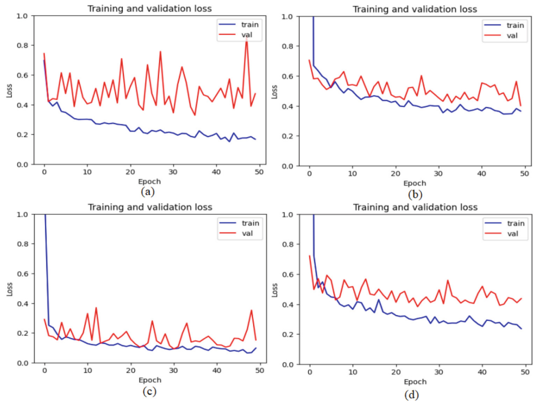

Fig. 3. Loss plots obtained for baseline models (a) MobileNetv2, (b) InceptionV3 (c) DenseNet201 and (d) XceptionNet on Maize leaf disease dataset

never got reduced and for InceptionV3 and XceptionNet models, the training and validation showed better convergence but the over-all validation loss never got lesser than 0.35 and 0.3. While for the DenseNet201 and EfficientNetB4 models also the model showed good convergence but EfficientNetB4 model had fewer fluctuations between a restricted loss range, allowing for better model learning.

Over all the proposed model achieved the minimum number of misclassification i.e. 27 for the dataset, thereby supporting the reliability of the model as presented in Fig. 4.

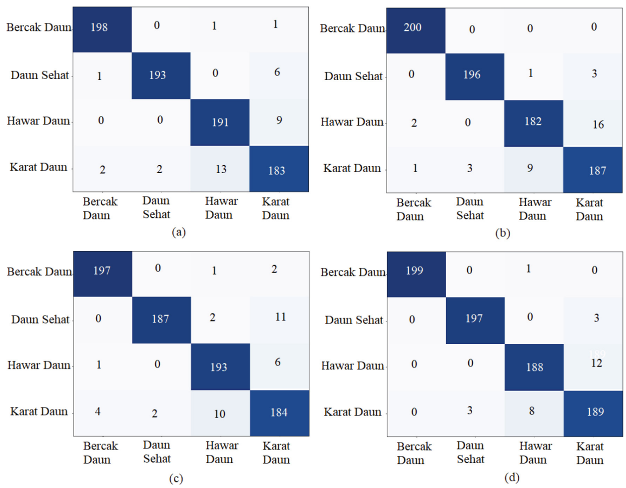

Fig. 4. Confusion matrices obtained for different combinations of Dense layers and multi-head attention layers applied for fine-tuning of EfficientNet-B4 model (a) without MHA layer,(b) with MHA layer after DL-1, (c) with MHA layer after DL-2 and (d) with MHA layers after DL-1 and DL-2

6 Conclusion

The paper proposed the novel classification model that integrated three dense layers and two multi-head attention layers for fine-tuning the architecture of EfficientNetB4 model for maize leaf disease detection. Multiple architectures comprising different combinations of dense and multi-head attention layers were tried and an alleviating change in accuracy and robustness of the model capabilities after a host of experiments was observed. Increased architectural depth through dense layers and feature weighting based on their relative importance allowed the distinction between healthy and diseased maize leaves effectively. The attention mechanisms particularly enabled the model to effectively focus on different regions in an input image adaptively, where it improves interpretability and decision-making of the proposed model against several other state-of-art networks. However, further work can be done to develop a unified system capable of classifying diseases in a variety of plants and crops at early stages for smart agricultural practices and effective management of crops.

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