EVALUATION OF THE GAMANNET CONVOLUTIONAL NEURAL NETWORK IN THE IDENTIFICATION OF FOLIAR DISEASES IN CORN

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ABSTRACT: Agriculture is of significant importance to Brazil's GDP, but global agricultural production is threatened by losses from plant health diseases. In this context, corn (*Zea mays* L.), the world's most widely produced cereal, requires efficient monitoring methods. This study evaluates the GamaNNet convolutional neural network in the automatic classification of leaf diseases in corn, using 3,852 images from the PlantVillage database, stratified into: asymptomatic leaves (1,162), Gray leaf spot (513), Common Rust (1,192), and Northern leaf blight (985). The model, implemented in Kaggle, has a 5-layer convolutional architecture plus 2 dense layers, trained for 100 epochs. The results revealed 95% overall accuracy, with optimal performance for Common Rust and healthy leaves (precision, recall, and F1-score = 1.00). However, Gray leaf spot showed lower sensitivity (recall: 0.79, F1-score: 0.83), while Northern leaf blight achieved an F1-score of 0.91. Compared to other models, GamaNNet shows operational viability in limited resources due to its architectural simplicity, although it needs improvements for Gray leaf spot identification. It is concluded that the approach offers fast and accurate detection, contributing to sustainable crop management.
KEYWORDS: *Zea mays* L., Computational intelligence, Image classification

AVALIAÇÃO DA REDE NEURAL CONVOLUCIONAL GAMANNET NA IDENTIFICAÇÃO DE DOENÇAS FOLIARES NO MILHO

RESUMO: A agricultura tem relevante importância para o PIB brasileiro, porém a produção agrícola global é ameaçada devido a perdas por doenças fitossanitárias. Neste contexto, o milho (*Zea mays* L.), cereal com maior produção mundial, demanda métodos eficientes de monitoramento. Este estudo avalia a rede neural convolucional GamaNNet na classificação

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automática de doenças foliares em milho, utilizando 3852 imagens do banco de dados PlantVillage, estratificadas em: folhas assintomáticas (1162), mancha cinzenta foliar (513), ferrugem do milho (1192) e mancha-de-helmintosporium (985). O modelo, implementado em Kaggle, possui arquitetura de 5 camadas convolucionais mais 2 camadas densas, treinado por 100 épocas. Os resultados revelaram 95% de acurácia global, com desempenho ideal para ferrugem do milho e folhas saudáveis (precisão, recall e F1-score = 1.00). Entretanto, mancha cinzenta foliar apresentou menor sensibilidade (recall: 0.79, F1-score: 0.83), enquanto mancha-de-helmintosporium atingiu F1-score de 0.91. Comparado a outros modelos, a GamaNNet mostra viabilidade operacional em recursos limitados devido à simplicidade arquitetônica, embora necessite de melhorias para identificação da mancha cinzenta foliar. Conclui-se que a abordagem oferece detecção rápida e precisa, contribuindo para o manejo sustentável de cultivos.

PALAVRAS-CHAVE: *Zea mays* L., Inteligência computacional, Classificação de imagens

INTRODUCTION

Agriculture plays a fundamental economic role in any country. In 2024, Brazilian agricultural production accounted for approximately 23.2% of the Gross Domestic Product (GDP) (Brazil, 2025). Population growth has a direct impact on food demand, affecting food and nutritional security. Corn (*Zea mays* L.) is one of the most widely grown cereals in the world, notable for its high productivity, the highest among cereals, and its great adaptability to different climates and cultivation systems. Its importance to society derives both from its nutritional value and its varied applications (Sah et al., 2020).

Corn is the most produced grain in the world, with more than 1.22 billion tons produced last year. Brazil is an important producer, ranking third in the world (USDA, 2025). It is estimated that plant diseases and pests cause losses of up to 40% of global agricultural production each year, in addition to causing costs associated with plant diseases of up to $220 billion per year (FAO, 2022).

Visual identification of leaf diseases early on is challenging because they look very similar. For an accurate diagnosis, both constant monitoring of crops and evaluation by a specialized team are necessary (Vijai & Mishra, 2017). This makes the conventional method expensive, time-consuming, and unreliable.

As an alternative, convolutional neural networks (CNN) enable the automatic, rapid, and accurate detection and classification of leaf diseases (Waheed et al., 2020). In this context, the present study aims to apply and evaluate the innovative CNN GamaNNet model in the visual classification of symptomatic corn foliage.

MATERIALS AND METHODS

PlantVillage is an international cooperation project that combines artificial intelligence and precision agriculture to support small farmers and extension workers. The project is developed in partnership with renowned institutions such as the Food and Agriculture Organization of the United Nations (FAO) and the Consultative Group on International Agricultural Research (CGIAR).

This program provides an open repository with more than 54,000 images of 14 crops, covering 38 phytosanitary problems. The images in the database are colored (RGB), with a resolution of 256 × 256 pixels. The present study used 3,852 images of corn leaf pathologies provided by PlantVillage. The samples were subdivided into four classes: (i) Asymptomatic (1162 images); (ii) Gray leaf spot (513 images); (iii) Common Rust (1192 images); and (iv) Northern leaf blight (985 images). Figure 1 shows individuais samples from the dataset.

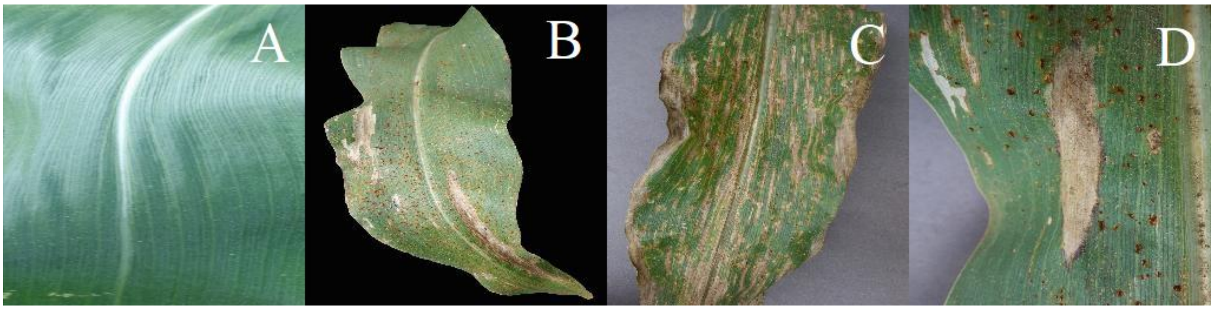

Figure 1. Leaf tissue of corn plants in the classes: (A) Asymptomatic; (B) Gray leaf spot; (C) Common Rust; (D) Northern leaf spot.

All stages of the study were carried out in a remote processing environment on the Kaggle platform, which provided access to an Nvidia Tesla P100 GPU (1.32 GHz, 9.526 TFlops) with 16 GB of RAM. To implement the deep learning strategies, the open-framework Keras and Tensorflow libraries were used in the supervised image classification task. The database was randomly stratified into three subsets: 64% for training, 16% for validation, and the remaining

20% for the testing phase, the latter being treated as a dataset not seen by the model during training.

The model used was GamaNNet (Oliveira et al., 2024), whose architecture consists of five convolution layers followed by max-pooling layers. The convolutional layers used 32, 64, 128, 256, and 512 filters, respectively, with a 2x2 kernel size in all of them. After each convolution layer, a max-pooling layer was also applied with a 2x2 window. The ReLu activation function was used in all these layers. At the end of feature extraction, the architecture has two dense (fully connected) layers. The first has 1028 neurons with ReLu activation, while the output layer has four neurons, one for each class, and uses the softmax activation function. For training, the loss function adopted was categorical cross-entropy, and the Adam optimizer was implemented to update the network weights. The batch size used was 32, with training performed in 100 epochs.

This article uses several evaluation metrics, such as precision (P), recall (S), and F1-score. To get an overview of the results, it is common to use the confusion matrix, a tool that evaluates the performance of a classification model by comparing actual classifications with predicted ones. It consists of four main elements: True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN). The performance metrics used are presented below:

$$\text{Accuracy} = (\frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{3}$$

$$\text{F1-score} = \frac{2\ x\ P\ x\ S}{P\ x\ S} \tag{4}$$

These components are fundamental for calculating key performance metrics, such as accuracy (which measures overall correctness), precision (which verifies the correctness of positive predictions), and recall (which evaluates the model's sensitivity in identifying positive instances). The confusion matrix provides a detailed analysis of prediction errors, offering deeper insights into model performance than accuracy alone (Malik et al., 2024).

RESULTS AND DISCUSSION

GamaNNet resulted in 26.393 million parameters, of which only 512 were not trained. Figure 1 illustrates the comparison of loss and accuracy for the training and validation sets throughout the training process.

In the analysis of the loss curves (Figure 1A), it can be observed that, for the training data, the loss remains low from the beginning and decreases progressively until reaching a final value of 0.0048. On the other hand, the loss curve for the validation data shows instability, with peaks and sharp drops that indicate that the model is not generalizing well. However, at the end of training, the loss for the validation set was 0.4384.

Regarding the accuracy curves (Figure 1B), the training set starts at approximately 67% and rises rapidly to values close to 90%, where it stabilizes. This demonstrates that the network has learned to classify the training data effectively and quickly. For the validation set, the accuracy showed fluctuations and abrupt drops, but overall remained slightly below the training accuracy. At the end of the epochs, the training and validation accuracy was 99% and 94%, respectively.

These results point to a common problem in convolutional neural networks (CNNs): overfitting. This phenomenon occurs when the model over-adjusts to the training data, resulting in unsatisfactory performance on unseen data. As highlighted by Rawat and Wang (2017), overfitting is a major challenge because it affects the model's generalization ability.

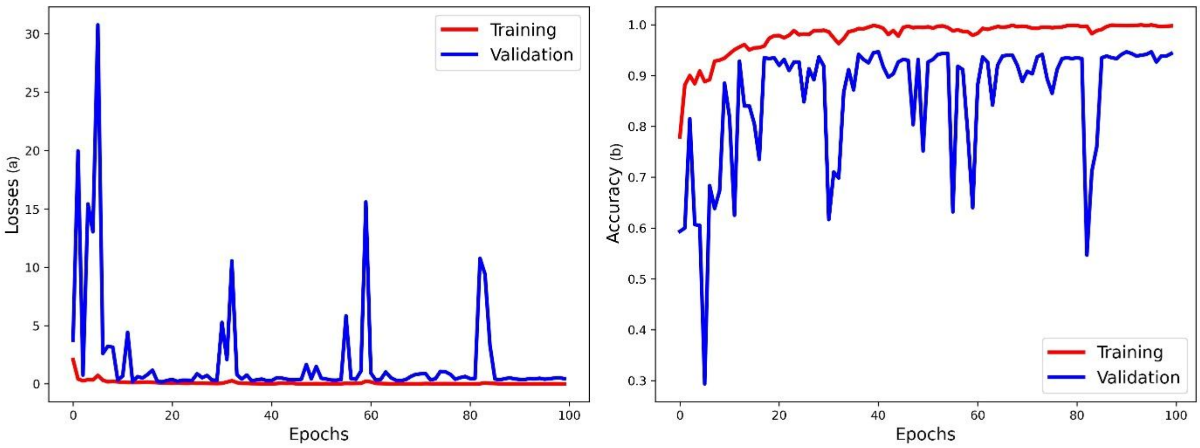

Figure 2. (a) Loss during GamaNNet training and validation; (b) Accuracy during GamaNNet training and validation.

The confusion matrix obtained for the GammaNNNet model (Figure 3) shows high overall performance in the classification of the four classes evaluated, which are Gray leaf spot (A), Common rust (B), Healthy (C), and Northern leaf blight (D).

It can be observed that most of the samples are correctly positioned on the main diagonal, indicating a high number of correct classifications. The Common rust and Healthy classes stand out for their perfect classification, with all 230 and 218 images, respectively, correctly identified.

For Gray leaf spot, 98 samples were correctly classified, but there were 26 cases confused with Northern leaf blight. The Northern leaf blight class had 186 correct classifications, but 13 samples were misclassified as Gray leaf spot. These errors suggest a visual similarity between these two diseases, which may have made it difficult for the model to distinguish between them.

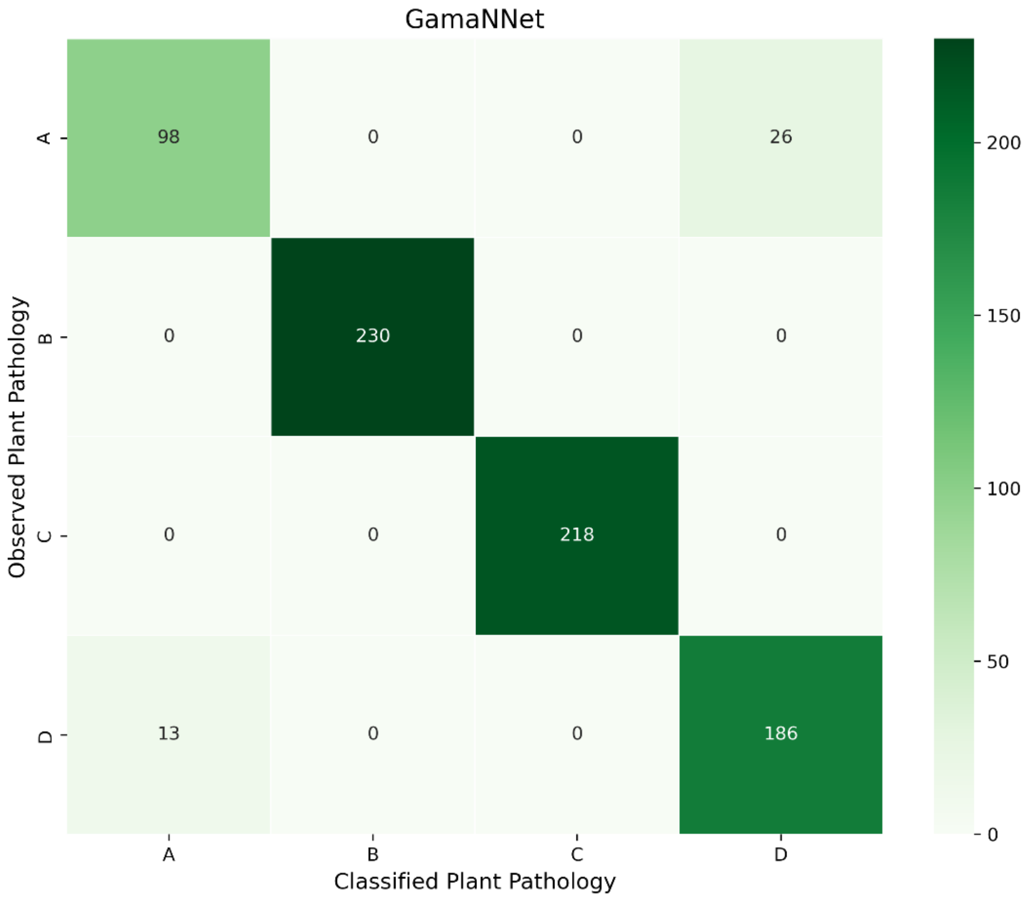

Figure 3. GamaNNet confusion matrix. Gray leaf spot (A); Common rust (B); Healthy (C); Northern leaf blight (D)

GamaNNet shows competitive performance in the task of classifying diseases in corn leaves. The overall accuracy of the current model was 95%, with perfect precision, recall, and F1-score (1.00) values for the Common rust and Healthy classes. In contrast, the Gray leaf spot class was the most challenging, with a recall of 0.79 and an F1-score of 0.83. The Northern leaf blight class also performed slightly worse, with a recall of 0.93 and an F1-score of 0.91 (Table 1).

Table 1. Classification report

	Precision	Recall	F1-score	Support
0	0.88	0.79	0.83	124
1	1.00	1.00	1.00	230
2	1.00	1.00	1.00	218
3	0.88	0.93	0.91	199
Macro avg	0.94	0.93	0.93	771
Weighted avg	0.95	0.95	0.95	771
Accuracy			0.95	771

Gray leaf spot (0); Common rust (1); Healthy (2); Northern leaf blight (3)

Similar to the present study, the works of Ouppaphan (2017) and Waheed et al. (2020) proposed different CNNs for the identification of corn pathologies (Gray leaf spot, Common rust, Northern leaf blight) in addition to differentiation with healthy leaves.

The model proposed by Ouppaphan (2017) achieved an overall accuracy of 97% and a more balanced performance between classes. Of particular note is the superior performance in the Gray leaf spot class, with a recall of 0.93 and an F1-score of 0.93, surpassing the results obtained by GamaNNet for this class.

The average performance metrics obtained by Ouppaphan (2017) were accuracy: 0.96, recall: 0.95, and F1 score: 0.95. These values are very similar to those obtained in the present study (0.94, 0.93, and 0.93, respectively), which reinforces the viability of the GamaNNet model.

In contrast, the results of Waheed et al. (2020) indicate superior performance, with an accuracy of 0.98 and a macro average F1 score of 0.97. The model performed excellently in all classes, especially for “Common rust” and “Healthy,” both with an F1 score of 1.00. The “Gray leaf spot” class, considered more challenging, also obtained an F1 score of 0.93, surpassing the result achieved in this study. The “Northern leaf spot” class was also well ranked, with an F1 score of 0.96. Despite these comparisons, the results of GamaNNet demonstrate great potential for the detection of leaf diseases in field applications.

CONCLUSIONS

Although the model used in this study shows slightly lower overall accuracy than the compared studies, it stands out for its high precision, computational simplicity, and excellent performance in two of the four classes. This makes it viable for practical applications, especially in scenarios with limited resources. The main improvement is in the detection of gray leaf spot.

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