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A Deep Learning Approach to Tomato Disease Classification Using a CNN-LSTM Hybrid Network

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Abstract- Our work proposes a classification architecture based on deep learning techniques, particularly convolutional and recurrent neural networks, for the classification of tomato diseases from digital images. More specifically, the objective is to classify leaves infected by a disease using supervised learning on a pre-labeled image dataset from PlantVillage. One of the main challenges of using deep learning, however, is the need for a very large amount of annotated data, which is not always available. Therefore, the objective of our study is to develop a specific hybrid architecture, CNN-LSTM (Convolutional Neural Networks - Long Short-Term Memory), capable of leveraging small (frugal) and relatively imbalanced datasets. To assess the relevance of this approach, we propose to compare it with deep learning algorithms frequently described in the literature. The proposed model achieved better classification performance in terms of validation Accuracy of 94,16%,

Index Terms- CNN-LSTM, hybrid, supervised, deep learning

I. INTRODUCTION

Tomatoes are one of the most economically important vegetable crops in the world, and growing methods have been continuously improved over the years. As a commercial and nutritious food crop, it plays a vital role in the agricultural economy [1] However, plant diseases cause considerable economic, agricultural and ecological losses, thus compromising safety [2 Tomato crops are particularly susceptible to diseases caused by various factors such as climatic conditions, insects, viruses and bacteria. These foliar diseases affect plant growth and production, resulting in notable agricultural losses. In some countries, they can account for between 10% and 20% of annual tomato production [3]. Therefore, early detection of diseases is crucial to prevent their spread and limit losses [4]. Image classification plays a key role in the identification and detection of leaf diseases, determining whether a leaf is infected or healthy [5]. Convolutional neural networks (CNNs) have become a preferred method for extracting relevant features from images, providing high accuracy in disease detection [6]. In particular, recent research has demonstrated the effectiveness of CNNs in identifying features such as texture, color, and patterns of affected leaves [7].

In addition, recurrent neural networks (RNNs), especially those integrating long and short memory units (LSTMs), are distinguished by their ability to process complex time sequences. These models are particularly suitable for tracking disease progression over several time periods[8]. The integration of CNNs and RNNs into hybrid architectures has significantly improved the detection and classification performance of foliar diseases [9].Our contribution In this research work:

In this study, we propose to exploit the analysis and extraction potential offered by the CNN combined with an LSTM architecture capable of memorizing, predicting and capturing long-term dependencies in data. This type of combination is not new and exists for video [10], text [11], ... Note the work of Wang et al.

[12] on SAR images from the MSTAR base, which proposes to exploit a CNN-LSTM network coupled with an attention module in the context of a multi-view problem of stationary ground targets. The originality of the approach described here is based on the development of a relatively different hybrid architecture (absence of an attention module, different structures and optimizations of the parameters and hyperparameters of the network) and, on the other hand, the realization of the disease recognition function from a database of Tomato images

We used pretrained a hybrid model, CNN_LSTM to detect a total of 10 diseases of Tomato .

The proposed Hybrid model CNN_LSTM and compared our results for Validation accuracy and for Training accuracy with other previous research's CNN and LSTM.

This work focuses on the use of a hybrid CNN- LSTM architecture for the classification of tomatoes in tomato leaf images . Section 2 explains the proposed methodology and model used and the steps taken to obtain the essential results. Section 3 deals with the

results and analysis of the proposed methodology. Section 4 includes the conclusion of the paper and provides the scope of future work.

II. LITERATURE

Plant diseases are a major problem in agriculture, reducing both the amount of food production and the quality of agricultural products [13]. Accurate diagnosis and proper management help protect plants from massive losses. Thus, plant disease detection techniques play a crucial role in protecting crops from rapid infection and promoting agricultural growth. The performance of these detection techniques is therefore essential [14]. This is why advanced techniques based on computer vision have been developed to compensate for the lack of human expertise [15]. In 2011, the neural network technique was implemented. It used the Otsu method, followed by feature extraction [16]. In 2012, the artificial neural network (ANN) classifier was used. The images were filtered using the Gabor filter, and then the values of the extracted features were trained with the classifier, achieving an accuracy of 91% [17]. Thus, in the agricultural field, deep convolutional neural networks (NNCs) are used for the recognition and classification of plant diseases [18]. A deep convolutional neural network architecture, trained with a machine learning-based model, has been proposed to predict tomato plant diseases [19]. Advances in CNNs have led to the development of deep CNN architectures, incorporating various pre-trained models like AlexNet, GoogleNet, DenseNet, ImageNET, VGGNet, and ResNet, which have been used to detect plant leaf diseases. In 2018, an architecture based on the deep CNN network with VGG was implemented to diagnose diseases, achieving 99.58% accuracy. This model proved to perform very well when trained well, outperforming other models [20].

In 2019, four deep CNN models were developed for tomato disease detection, including the Mask R-CNN and Faster R-CNN models for object detection [21]. A pre-trained CNN model combined with an LSTM was implemented to detect apple pests and diseases, outperforming deep CNN architectures [22]. In 2020, a robust model based on the RNN architecture was introduced to rapidly detect infected areas of plants [23].

III. METHOD PRPOSAL

The previously implemented traditional leaf disease detection models classified the diseases with better performance. These implementations indicateneed for early detection. However, those existing models failed to detect the disease in earlier stage.

In this paper, a hybrid method is developed to identify the type of diseases from images of tomato leaves. Figure 3 illustrates the architecture designed by combining two networks: Convolutional Neural

Networks (CNN) and Long Short-Term Memory (LSTM). CNN is used to extract complex features from images and LSTM is used as a classifier. The description of the architecture is described in Table 2.

1. Architecture CNN

The architecture for classifying tomato diseases consists of three convolutional layers, each followed by a max-pooling layer, which allows for the efficient extraction of relevant features, and a Dropout layer to prevent overfitting. After these operations, a Flatten layer prepares the data for processing by a fully connected layer, facilitating the fusion of the extracted features before the final classification. The model is designed to classify then distinct classes, corresponding to the condition of the tomato leaves (Figure 1). The hyperparameters (HP) selected for optimization include the number of filters in each convolutional layer, the abort rate, the learning rate, the batch size, and the number of epochs. the activation function used in the convolutional layers is ReLU, ensuring non-linear transformations and efficient gradient propagation. The optimizer chosen for training is Adam, known for its adaptability and faster convergence in deep learning models. The model's performance is evaluated using accuracy, precision, recall, and F1-score to ensure a robust assessment of classification quality. Furthermore, early stopping is implemented during training to prevent overfitting and optimize the training process.

2. Description of our Model

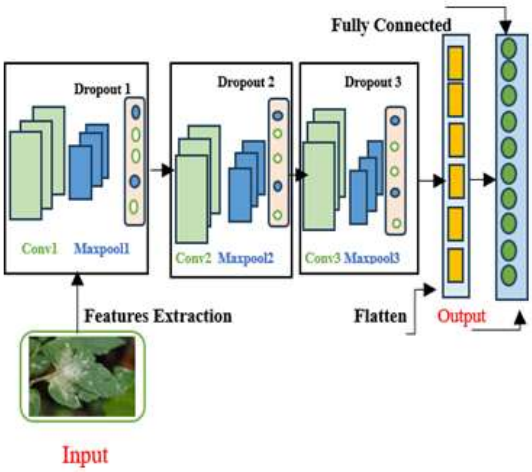

Figure 1- Architecture CNN

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The CNN model designed for tomato leaf disease detection consists of three convolutional layers with filters of increasing sizes (32, 64, 128), using the ReLU activation function and followed by layers of

MaxPooling (2×22 \times 22×2) to reduce the dimensions. To limit overfitting, dropout layers with rates of 0.25 (convolutional) and 0.5 (dense) are integrated. The feature maps are flattened before being processed by two dense layers (256 and 128 neurons) and a 10-neuron Softmax output layer for multiclass classification. The model is trained with the Adam optimizer, a loss of categorical crossentropy, and an accuracy metric. It uses a batch size of 32 out of 100 epochs for a balance between accuracy and efficiency.

3. Architecture LSTM

LSTM networks are recurrent neural networks that are particularly suitable for processing sequential data. They are designed to capture long-term temporal dependencies by using memory cells that allow relevant information to be retained over long sequences. Thanks to their unique structure, LSTMs are able to handle gradient problems that can occur in classical recurrent networks. In our work we used a stacked LSTM network of two layers to analyze temporal data.

The architecture of our LSTM model included two single LSTM layers equipped with 128 units and 64 units respectively followed by a dense layer exploiting softmax activation to produce output probabilities for each class. Subsequently, the model was compiled using the Adam optimizer and the categorical cross- entropy loss function, with precision serving as the primary measure of evaluation. The LSTM model was then trained on the redesigned training dataset. Throughout the training process, the model skillfully assimilated the temporal dependencies within the input sequences, allowing it to make accurate predictions regarding the presence of various tomato leaf diseases.

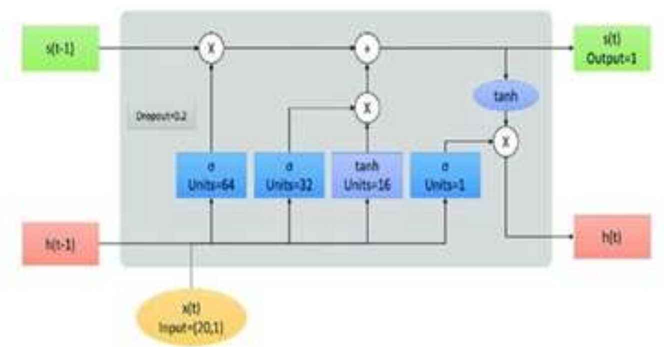

Figure 2- Architecture LSTM

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Architecture CNN-LSTM

In Our paper, an innovative hybrid method we proposed to identify the types of tomato leaf diseases using images from the PlantVillage database. Figure 1 illustrates the architecture of the method, which combines two popular neural network models: Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. The CNN is used to extract complex and relevant features from the images, while the LSTM serves as a classifier, analyzing the extracted features to produce a robust classification. A detailed description of this architecture is provided in Table 2. The hybrid CNN-LSTM architecture is an interesting solution for the classification of tomato diseases, as it combines the advantages of CNNs and LSTMs. On the one hand, CNNs are integrated for their ability to identify and extract specific features from input data. The CNN comprises three blocks, each including a convolutional layer, an activation function, and a pooling function. These blocks also incorporate Dropout layers to prevent overfitting and improve model generalization. On the other hand, LSTMs are particularly effective at capturing dependencies in data sequences, thanks to their ability to remember information over long periods and process sequences with long-term dependencies.

These networks employ memory cells and gate mechanisms to prevent the vanishing gradient problem, thereby enabling better retention of relevant information over time. The hyperparameters selected for optimization include the number of filters in each of the three convolutional layers of the CNN and the number of units in the LSTM layers of the LSTM network.

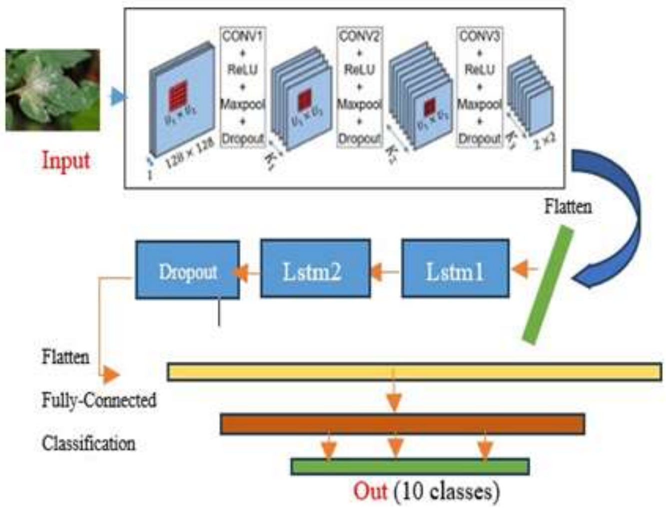

Figure 3- Architecture du CNN-LSTM

Hyper Ps to be Optimized

La structure des reseaux de neurones comporte un grand number of HP (Table 1) .the first category is related to the configuration of the model . Since all neural network models have an input layer and an output layer, the complexity of a DNN model depends mainly on the number of hidden layers and the number of neurons in each layer, which are the two main performance factors from a model architecture perspective. These are defined and adapted according to the complexity of the data.the capacity of the models must be sufficient to model bjective functions (or prediction tasks) by avoiding overfitting. Then some types of functions have to be determined or ajustés.la first to be configured is the type of the loss function, which is mainly chosen according to the type of problem (binary cross-entropy for multiclass classification problems and RMSE for regression problems). In addition, some HP parameters such as the number of filters and the kernel size are key HPs for CNN-type networks. The number of filters influences the extracted characteristics, the kernel size acts on the spatial dimension of the learned models and the size of the pooling allows to reduce the spatial dimension while preserving the essential characteristics. These hyperparameters play a critical role in the model's ability to extract relevant information and control the dimensionality of the data. Another important feature of HPs is the type of nonlinear activation function employed, which can be defined as Rectified Linear Unit (ReLu), Sigmoid or Hyperbolic Tangent (tanh). Finally, the type of optimizer can also vary: SGD, Adam, Rmsprop, etc. In addition, some other HP are associated with the learning process of DNN models. The learning rate is one of the essential HP of DNN models [24] The latter determines the length of the steps at each iteration of gradient descent, which plays an essential role in the convergence of the models. A high learning rate accelerates the learning process, however the gradient may oscillate around a local minimum, or not converge at all. On the other hand, a low learning rate favours regular convergence, but considerably increases the training time of the model by requiring more epochs for learning. Another common hyper rameter is the dropout rate. Dropout is a classic method of egularization of DL models. Intended to reduce overfitting. During this operation, the updating of the weights of some of the neurons is randomly inhibited. In our work, we focus on the optimization of the HP of the different architectures using several optimization algorithms, in particular the HP of the different architectures using several optimization algorithms, in particular GS, RS and TPE.Table 1 below, detailing the HP to be optimized for each architecture, namely CNN, LSTM, CNN_LSTM, as well as the search space defined for our model CNN_LSTM the step used is the number of layers The number of units used in the HPs is the learning rate, chosen for all the architectures, the number of filters for architectures based on convolutional networks, namely the CNN and CNN_LSTM, as well as the number of units in the LSTM layers for the LSTM and AE_LSTM architectures.

In our research, we have created three hybrid models CNN_LSTM1, CNN_LSTM2 and CNN_LSTM3 where each time we modify the numbers of layers of LSTM and the number of epochs. After several trainings we obtained a better perfermant model which has the parameters illustrated in Table 1, this model is tested on a public dataset which contains a set of tomato images which will be divided into two parts: 20% is designated for validation and 80% is designated for training. then we compared our model with the CNN and LSTM model AND with other research .

Table 1.The parameters used in Our Hybrid Cnn_Lstm model and in the configuration

Category	Parameter	Recommended value
Data Augmentation	rotation_range	30
	width_shift_range	0.3
	height_shift_range	0.3
	shear_range	0.2
	zoom_range	0.2
	horizontal_flip	True
	fill_mode	nearest
	validation_split	0.2
CNN	Couche 1 : Conv2D	32 filtres, (3,3), ReLU
	Couche 2 : Conv2D	64 filtres, (3,3), ReLU
	Couche 3 : Conv2D	128 filtres, (3,3), ReLU
	MaxPooling2D	(2,2)
	Dropout	0.5 (1ère couche), 0.5 (2) et 0.5 (3)
LSTM	Reshape	(1, -1)
	LSTM	128 unités
	LSTM	64 unités
	Dropout	0.5
Output layer	Dense	10 unités, activation softmax
Compilation	Optimizer	Adam, learning_rate=0.0001
	Loss	categorical_crossentropy
	Metrics	accuracy
Training	batch_size	32
	steps_per_epoch	samples // batch_size
	epochs	100

Data Collection
This dataset consists of a total of 22930 images of tomatoes in ten different states: bacterial spots, mosaic viruses, target spots, tomato yellow leaf curl viruses, late blights, spider mites (two-spotted spider mites), healthy tomato, and sectorial leaf spots. This dataset can be used for image classification tasks, particularly for identifying the disease of tomatoes. The images were carefully selected to ensure a diverse range of tomato diseases the dataset is publicly accessible .

Image Pre-processing

From the total collected dataset, we have selected approximately 22930 images divised on 18345 for training and 4585 for validation to be used in this research. To facilitate the training process, we have divided the dataset into separate test and train folders, with a ratio of 20% for testing et validation and 80% for training. The diseases present in the dataset have been organized into separate categories based on their names, enabling easy differentiation between them. To optimize computational efficiency without compromising image quality, we have resized all the images to dimensions of (128x128) pixels. This resizing allows for faster computations while ensuring that the integrity and details of the images are preserved.

Image Augmentation

Image augmentation is a method employed to create numerous versions of one image. This research implements picture augmentation, applying the following alterations to the images: The objective of this proposed method is to modify, streamline, and improve photographs in a clear and accessible way.

- By simplifying and altering the representation of the images, we can create a diverse set of new images, thereby enriching the dataset.
- The model employs various transformations on the images, including rotation within a range of 30 degrees, horizontal and vertical shifts with ranges of 0.3 resizing to a scale of 1/155, shearing within a range of 0.2, and zooming within a range of 0.2. Additionally, horizontal flipping is also used to improve the accuracy, with the filling mode set to 'nearest'.
- The 'Rescale' parameter is a numeric value applied during data processing. It effectively scales down the pixel values of the RGB images, which originally range from 0 to 255, to values between 0 and 1. This scaling is necessary for optimal performance during the model's training process, especially when using a typical learning rate.
- The rotation angle follows a counter clockwise direction and is controlled by the shear range. Images after Augmentation is shown below in Figure 4

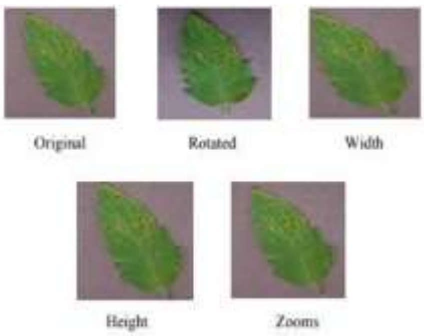

Figure 4 -Augmented Images

IV. RESULTS AND DISCUSSIONS

1. A.Resulats

In the context of classifying diseases from tomato leaf images, the performance of three distinct models CNN, LSTM, and the hybrid CNN-LSTM model was thoroughly evaluated on the publicly available PlantVillage dataset. The evaluation was based on various metrics, such as accuracy, Validation accuracy, loss and validation loss . The hybrid CNN-LSTM model proved to be the most effective, likely due to its ability to combine the spatial feature extraction capabilities of CNNs with the temporal dependency modeling of LSTMs.

Table 3. Experimental Results of the three hybrid Cnn_Lstm model tested with various parameters for hyper- parameter model tuning.

Model	Number of epochs	Loss	Accuracy	Val_loss	Val_accuracy
Hybrid Model1 Cnn_Lstm	10	0.5528	0.8438	0.3484	0.8758
	20	0.1849	0.9688	0.3418	0.8805
	30	0.2526	0.9375	0.2388	0.9178
	60	0.2360	0.9062	0.2360	0.9323
Hybrid Model2 Cnn_Lstm	30	0.92	0.6250	0.6311	0.7667
Hybrid Model3 Cnn_Lstm	100	0.1485	0.9517	0.1866	0.9416

This allowed it to achieve an impressive accuracy of 95.17 % with 100 epochs . These promising results suggest that the hybrid CNN- LSTM model could be a highly effective solution for designing more robust and accurate diagnostic and classification systems. It is noteworthy that this hybrid approach outperformed the standalone CNN and LSTM models, which achieved respective accuracies of 92.11% and 83.33%. Furthermore, the CNN-LSTM model demonstrated superior precision and recall values, surpassing its counterparts with a precision of 94.16% and val_loss 18.66%.

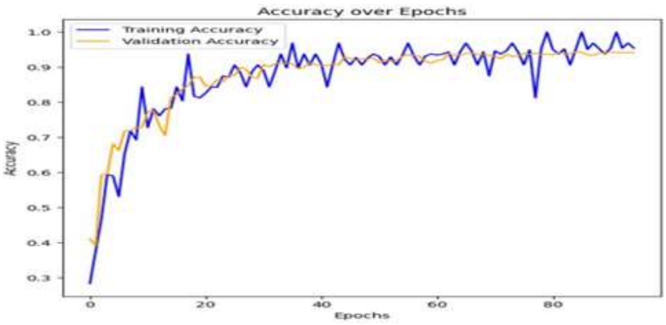

Figure .5 loss and validation loss of CNN_LSTM model

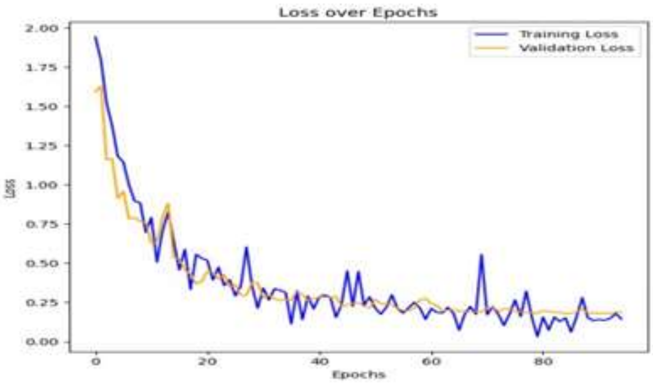

Figure 6- training and validation accuracy for CNN_LSTM model

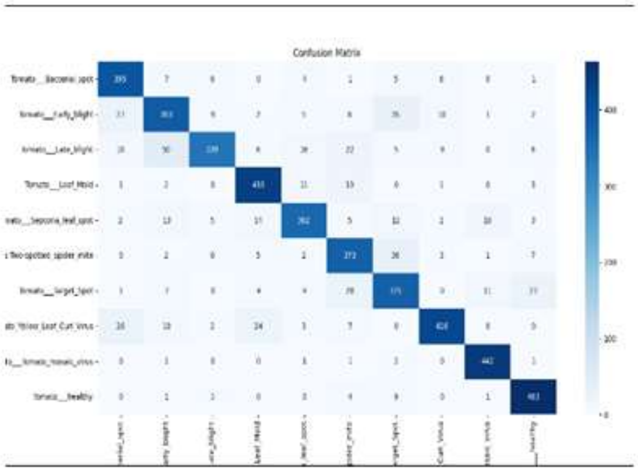

Figure 7- Confusion Matrix for CNN_LSTM model

Classification Report:

	precision	recall	f1-score	support
Tomato___Bacterial_spot	0.09	0.09	0.09	425
Tomato___Early_blight	0.09	0.11	0.10	480
Tomato___Late_blight	0.10	0.09	0.09	463
Tomato___Leaf_Mold	0.09	0.09	0.09	470
Tomato___Septoria_leaf_spot	0.10	0.08	0.09	436
Tomato___Spider_mites Two-spotted_spider_mite	0.10	0.09	0.10	435
Tomato___Target_Spot	0.09	0.06	0.07	457
Tomato___Tomato_Yellow_Leaf_Curl_Virus	0.11	0.10	0.10	490
Tomato___Tomato_mosaic_virus	0.07	0.08	0.07	448
Tomato___healthy	0.09	0.13	0.10	481
accuracy			0.09	4585
macro avg	0.09	0.09	0.09	4585
weighted avg	0.09	0.09	0.09	4585

Figure 8- Report classification for CNN LSTM model

Table 3.Comparison table between three models

Model	Number of epochs	Loss	Accuracy	Val_loss	Val_accuracy
CNN_LSTM	100	0.1485	0.9517	0.1866	0.9416
CNN	100	0.1861	0.9375	0.2336	0.9211
LSTM	100	0.4417	0.8548	0.4936	0.8333

The table shows a comparison between three models: Hybrid Model3 (Enhanced CNN-LSTM), CNN alone, and LSTM alone, in terms of training and validation metrics (Loss, Accuracy, Val_Loss, Val_Accuracy) after 100 epochs.

Hybrid Model3 (Enhanced CNN-LSTM)
This model has the best overall performance with a validation accuracy (Val_Accuracy) of 94.16% and a validation loss (Val_Loss) of 0.1866, showing its ability to generalize well on test data. This indicates that the enhanced CNN-LSTM combination effectively captures both spatial and temporal features.

CNN Alone
With a validation accuracy of 92.11% and a Val_Loss of 0.2336, the CNN performs well, but remains below the Hybrid Model3. This suggests that, while it excels at extracting spatial features, it lacks temporal or sequential understanding.

LSTM Seul
Ce modèle est nettement inférieur, avec une précision de validation de 83.33% et une Val_Loss de 0.4936, ce qui indique une difficulté à traiter les données d'image sans prétraitement spatial (comme effectué par un CNN).
Le modèle hybride CNN-LSTM amélioré (Hybrid Model3) surpasse les architectures CNN et LSTM seules en exploitant leurs forces respectives. Perspectives: Les futures améliorations pourraient inclure l'ajout de mécanismes d'attention ou de Transformers pour renforcer encore la capture des relations complexes dans les données.

Comparison to Other Research
Compared to other research, the Hybrid Model3 (enhanced CNN-LSTM) outperforms previous works. For instance, [25] used a standard CNN model for tomato disease detection, achieving a validation accuracy of 91.5%. Similarly, [26] proposed an LSTM- only architecture, reaching 84% accuracy, which aligns with the limitations observed in our LSTM model. In contrast, Hybrid Model3 leverages both spatial and temporal features, achieving 94.16% accuracy. These results highlight the advantages of hybrid approaches for complex tasks like plant disease classification

V. CONCLUSION

In this article, a hybrid CNN-LSTM architecture is proposed and its performance is analyzed as part of the classification of tomato diseases from the public database PlantVillage which presents several types of plant diseases data. In order to optimize the choice of certain hyper-parameters, a set of simulations is carried out in order to select the appropriate and optimal configuration to obtain the best possible generalization performance. The performance of the CNN-LSTM is compared to several architectures frequently used in the field of optical image processing. It turns out that the results in terms of classification performance and training time, model size (number of parameters) show the real interest of replacing the classic dense layers of CNNs with an LSTM layer for the classification of tomato leaf images. It would be interesting to validate this approach in the context of other databases. To go further, the use of more complex architectures could be studied. In particular, the use of these architectures combined with an attention mechanism could be used to select the relevant parts of the images and orient the network during the feature extraction phase.

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