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Enhancing Tomato Plant Leaf Diseases Detection through Ensemble of Deep Learning Models: A Survey.

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ABSTRACT: Agriculture forms the foundation of Zimbabwe's economy. Farmers can face economic losses if they fail to identify diseases in their tomato plants or give them the wrong treatments after making incorrect assumptions. Hiring experts to inspect tomato plants and identify diseases can be expensive, so it is essential to use technology. Extensive research in the agriculture industry has shown that plant diseases are among the factors responsible for reducing the overall productivity of crops. The use of Deep Learning has led to significant advancements in the performance and accuracy of object detection and recognition systems. These advancements have made it possible to predict leaf diseases in crops faster and more accurately. Such improvements are vital as they help develop early treatment techniques, subsequently leading to significant reductions in economic losses associated with crop diseases. According to research, deep learning provides high accuracy, surpassing existing commonly used image processing techniques.

KEYWORDS: Deep Learning; Convolutional Neural Network (CNN); Ensemble; hyperparameters; feature Extraction; Image processing.

I. INTRODUCTION

The economy of Zimbabwe heavily depends on a thriving agricultural sector, especially the tomato industry, which is a crucial and widely consumed crop [1]. Nonetheless, tomato cultivation faces difficulties due to disease outbreaks that can adversely affect the quality and quantity of crops. [2]. Accurately detecting and categorizing diseases on tomato leaves is crucial to minimize losses and optimize production. Historically, experts have relied on visual inspection of plants to identify diseases, which is a costly and time-consuming process. In recent times, researchers have explored automated disease classification using machine learning algorithms in computer vision. However, these approaches require laborious manual feature engineering, which makes them both expensive and time-consuming.

Deep learning [3], especially CNN is a potential solution that can extract features from images automatically, addressing the shortcomings of traditional machine learning. When it comes to classifying plant diseases, CNN models are excellent because they learn high-level features directly from images. Hyperparameter optimization is critical to achieving the best possible performance with deep learning models.

The primary aim of this study is to classify tomato leaf diseases using deep learning models. CNNs' automatic feature extraction capabilities can overcome the limitations of traditional machine learning methods. To enhance the disease detection accuracy, the researchers propose an ensemble of multiple deep learning models. Ensemble learning combines these models' predictions to achieve more robust and accurate results. By aggregating the outputs of various deep learning models, each trained on different aspects of the data, a comprehensive understanding of tomato leaf diseases can be obtained. This approach reduces the dependence on individual hyperparameter settings and improves the overall classification system's robustness. The research will use a Kaggle dataset that includes ten different tomato diseases, enabling a comprehensive evaluation of the proposed ensemble deep learning methodology under various

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conditions. The ultimate goal is to develop more efficient and accurate systems for early detection and classification of tomato leaf diseases, promoting sustainable agricultural production.

II. RELATED WORK

There are different algorithms and methodologies for identifying the disease on plant leaves. There are many different organizations and researchers who have studied and done work on this topic using different algorithms. Some of them are summarized below:

In 2023, P. Gweme et al. [4], developed a predictive model for identifying tomato plant leaf diseases. They utilized deep learning algorithms such as CNN and resNet, fine-tuning the hyper-parameters to enhance the accuracy of the predictions. They obtained a dataset from Kaggle and were able to achieve an accuracy rate of 90%.

In October 2023, Theodora Sanida et al. [5] used CNN on the identification of plant diseases in tomatoes. They used transfer learning to improve the accuracy of the model and reduce the training time. The VGGNet architecture, which had been pre-trained using ImageNet, served as the basis for the model and included two inception blocks.

Shima Ramesh, et al., researched that 42% of agriculture production suffers losses due to plant leaf diseases. 3C technique was used to detect these diseases from input images. The technique involves three main steps: image pre-processing, image segmentation, and feature extraction. After these steps are completed, KNN classification is applied to classify the disease [6]

In 2022, Priyanka N. Bande and Mr. Kranti Dewangan investigated the application of deep learning models in precise farming for detecting and classifying plant diseases. In their study, they have employed various deep learning models such as VGG-16, ResNet-50, AlexNet, DenseNet-169, and InceptionV3 for automatically diagnosing plant diseases, using Plant Village Dataset for training and testing these models. ResNet-50 achieved the highest accuracy of 97.80% [7].

In April 2023, S. Srinivas et al. proposed a system that uses the Inception V3 model to identify and classify diseases in tomato leaves, using an online Kaggle dataset [8]. June 2023, Samuel Giftson Durai et al., used CNN and ResNet50 for image segmentation to detect early blight and late blight potato infections from leaf images. They achieved a high accuracy of 99.75% [9].

S. S. Harakannanavar et al., in 2022, researched four models VGG-19, VGG-16, Res-Net, and Inception V3, evaluating their performance on two different datasets. The first dataset consisted of controlled images acquired in a laboratory, while the second dataset was collected from the field under natural light conditions using a cell phone. The second dataset was found to be more challenging for various pre-trained neural network models as it was representative of a real-world situation. The authors observed that parameter tuning produced more accurate results than feature extraction. They also found that the average performance on the laboratory-based dataset was 10% - 15% better than on the field-based dataset [10].

III. PROPOSED DEEP LEARNING APPROACHES

Within the field of machine learning, deep learning focuses on teaching artificial neural networks to learn, predict, or make decisions without requiring explicit programming [3]. It draws inspiration from the architecture and operations of the human brain, especially from its intricate network of neurons.

1. VGG: VGG-16 was developed at the University of Oxford, it is a convolutional neural network architecture with 16 layers, 13 convolutional layers, and 3 fully connected layers. It has a uniform architecture and is known for its simplicity, with 3x3 convolutional filters used throughout the network. Its performance in various image classification benchmarks has been exceptional. [11], [12].

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2. InceptionV3, known as Google Net, is a deep CNN convolutional neural network architecture developed by Google. It won the ImageNet_Large-Scale_Visual_Recognition_Challenge (ILSVRC) in 2014. InceptionV3 presented the idea of "inception modules" which are made up of several parallel convolutional layers that have varying filter sizes. This design enables the network to capture features at different scales and produce accurate results [12][8].

3. ResNet-101 is a "Residual Network." It introduced skip connections or residual connections, which help the network learn residual mappings, solving the vanishing gradient problem and allowing for the training of much deeper networks. ResNet-101 is composed of 101 layers and has displayed exceptional performance on various image classification tasks, including the ImageNet challenge [12].

4. DenseNet121 is for deep CNN that prioritizes strong feature connectivity and reuse. Each layer in DenseNet is connected to all other layers in a feed-forward manner, promoting feature propagation and reuse. This dense connectivity helps mitigate the vanishing gradient problem and improves gradient flow during training. With 121 layers, DenseNet121 has been demonstrated to perform competitively on tasks involving image classification [12].

5. Xception is an architecture that is based on Inception, but with a focus on depth-wise separable convolutions. It replaces the standard convolutions in Inception modules with depth-wise separable convolutions, which handle spatial and channel-wise convolutions separately. By doing so, it reduces computational complexity and enables more efficient and accurate feature extraction. [12].

Ensemble Approaches in Deep learning

Ensemble methods are useful in classifying tomato plant diseases since they amalgamate multiple models to enhance accuracy and stability. Ensemble learning is a technique that combines various models to obtain improved generalized performance, making them more effective than shallow or traditional models by merging the advantages of both deep learning models and ensemble learning [13]. There are various categories into which ensemble models can be divided, including bagging, boosting, stacking, negative Deep ensemble models based on correlations, explicit/implicit, homogeneous/heterogeneous, and decision fusion procedures are employed.

1. A voting ensemble involves training several models independently on the same dataset. The predictions of these models are then combined using either majority or weighted voting. Each model can be assigned equal or different weights, and the final prediction is made based on the aggregated votes. Voting ensembles can be useful in mitigating the impact of individual model biases and ultimately improving the overall classification accuracy. [14].

2. Bootstrap Aggregating, also known as Bagging, is a technique used to train multiple models on different samples of training data. Each model is trained separately, and their predictions are combined through majority voting or averaging. By using different samples, Bagging reduces overfitting and improves the generalization capability of the ensemble.

3. Boosting is an ensemble technique that involves training multiple models sequentially, with each subsequent model focusing on correcting the mistakes made by the previous models. During training, boosting algorithms like AdaBoost and Gradient Boosting assign higher weights to misclassified samples to emphasize their importance. Typically, the final prediction is determined by a weighted combination of predictions from all the models. Boosting can be used to improve both accuracy and model robustness.

4. Stacking is a technique that involves combining the predictions of several models by training a meta-model that bases its predictions on the outputs of the individual models. The models used for this purpose are called base models, and the meta-model uses their predictions as input features. This method allows for a more advanced combination of models and enables the capture of higher-order relationships between their predictions.

5. Random Forest is an ensemble technique that merges multiple decision trees. The training of each tree is based on a random subset of features and training data. The final prediction is generated by taking the majority vote or

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average of the predictions from all trees. Random Forests are renowned for their robustness, scalability, and capability to handle high-dimensional data.

6. An adaptive weighted ensemble is a type of ensemble learning where the weights assigned to each model's predictions are adjusted dynamically based on their performance. The ensemble adjusts the weights assigned to each model based on their performance on a validation set or the level of confidence. Models that perform well or have higher confidence are given higher weights, whereas poorly performing models are given lower weights. The ability to adjust the weights based on individual models' strengths and weaknesses allows the adaptive weighted ensemble to improve classification accuracy.

7. ECOC is a technique that can be used to solve multi-class classification problems by converting them into multiple binary classification sub-problems. To achieve this transformation, each individual binary classifier is trained to differentiate between a specific pair of classes. To determine the final class label, the predictions of all binary classifiers are combined through coding matrices. One of the benefits of ECOC is that it can enhance classification accuracy and effectively address complex multi-class problems [14].

IV. METHODOLOGY

The detection of plant leaf diseases on tomato plants could be improved by implementing convolutional neural networks, according to this study. The proposed methodology relies on pre-existing RGB images of plant leaves that have been labelled according to disease category. The use of labeled data facilitates model training through a supervised approach. To evaluate the model's performance, classification performance metrics such as the F1 score, recall score, accuracy, and precision will be employed.

1. Data Collection: Compile a diverse dataset of tomato plant leaf photos.
2. Data Pre-processing: Clean and pre-process the dataset for consistency.
3. Feature Extraction: Use CNNs for automatic extraction of relevant features.
4. Model Training: Utilize deep learning architectures like Res-Net or Inception.
5. Model Evaluation: Assess the model's performance using accuracy metrics.
6. Algorithm Deployment: Develop a user-friendly interface for practical adoption.

V. CONCLUSION AND FUTURE WORK

This survey paper covers various deep-learning techniques. The paper evaluates the use of deep learning methods in disease identification and classification by researchers. The survey highlights the reasons why deep learning approaches are superior in computer vision. The paper proposes an early disease detection approach to identify tomato leaf disease using a hybrid deep-learning model with ensemble methods. These deep learning techniques can help the system identify diseases on tomato plant leaves through image processing and provide a detailed diagnosis to farmers, along with specifying the necessary medicine to cure it. By utilizing ensemble methods, the aim is to achieve higher accuracy than individual models, as ensembles combine the predictions of multiple models to reduce errors caused by individual model biases or limitations.

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