Chapter 7
CropVigil:
Tomato Leaf Disease Detection Using Deep InfoMax Algorithm

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ABSTRACT

Modern agricultural approaches classify and eradicate tomato-weakening pathogens using classification systems. To increase output and ensure farming's survival, these diseases must be appropriately diagnosed. The disease's multi-symptom nature, the need for vast amounts of annotated data, and real-time execution complicate this technique. Deep InfoMax algorithm (DIMA) improves disease classification with deep learning, this method retrieves lots of data by training a deep neural network on tomato leaves. The network correctly classifies tomato leaf images as disease kinds after training. This technology is versatile enough for disease diagnosis, crop management, and yield optimisation. Detecting and treating leaf diseases improves tomato productivity and health. The suggested method will be confirmed through simulation studies conducted on different images of tomato leaf diseases, the method will be validated in this way. The present study's overarching goal is to demonstrate how DIMA may dramatically improve agricultural disease management

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INTRODUCTION

The manual inspection of tomato leaves is used to diagnose infections in tomato leaves (Chowdhury et al., 2021). Farmers and other agricultural specialists can identify anomalies in growth, discolouration, and spots on plants by carefully examining them, assuming that the inspector possesses the requisite knowledge, experience, and time to finish the procedure (Chowdhury). Several factors, including exhaustion, ineptitude, or human error, could contribute to the inconsistency of disease detection (Moussafir et al., 2022). Despite these approaches being successful, they cannot be implemented on large farms because it is impossible to individually monitor each plant (Trivedi et al., 2021). Analyses of pigments, edges, and thresholds use automated detection in their respective processes (Chopra et al., 2021). These approaches are unaffected by changes in sunshine, leaf orientation, or any other environmental circumstances, even though disease symptoms vary depending on the tomato species and the ripening stage (Rodriguez et al., 2021). When applying these methods, it becomes difficult to differentiate between diseases with the same visual symptoms (Kaur et al., 2022). This can lead to a diagnosis that is either inadequate or wrong because it is difficult to identify details in surroundings that contain plants, soil, and shadows. With time, the labour becomes increasingly challenging and intricate (Harakannanavar et al., 2022). It is impossible to effectively manage disease transmission and crop loss using current approaches since detecting diseases is slow and imprecise (Li et al., 2023). Current agricultural operations must implement more advanced and flexible approaches, such as the Deep InfoMax algorithm, to improve the efficiency and accuracy of identifying tomato leaf diseases.

The Deep InfoMax algorithm improves tomato leaf disease identification; however, several issues must be fixed before this technique can be widely used. One of the biggest challenges is that algorithm training requires massive tagged datasets (Zhou et al., 2021). Large databases take time to amplify and categorize; different agricultural techniques increase tomato plant disease risk. Humidity, sunlight, and soil type affect the look of damaged leaves and algorithm performance. Due to this variability, maintaining homogeneity across areas or growing seasons may be problematic. The model's complexity may make it hard to find processing capacity in rural or underdeveloped agricultural areas (Basavaiah et al., 2020). Deep InfoMax, which uses more processors, requires additional effort; due to this constraint, the algorithm may have trouble making decisions and identifying illnesses in real time. The system appears to be effective at observing patterns in current illnesses; however, it may not be able to forecast future illnesses due to a lack of training data. When employing the Deep InfoMax system for agriculture, its ease of use and accessibility may affect its disease diagnosis accuracy (Zhao et al., 2021). Farmers and farmhands may struggle with machine-learning algorithms. To successfully balance their daily responsibilities, farmers must find simple techniques they can adopt. Deep InfoMax can improve crop health and yield if the agriculture sector addresses these issues.

As a result of the Deep InfoMax algorithm's inability to accurately identify diseases in tomato leaves, several potential solutions have taken shape. Utilizing input augmentation and transfer learning, which enhance the resilience of models on smaller datasets with more varied input, can help reduce the requirement for enormous labelled datasets. This can be accomplished by reducing the amount of data that needs to be labelled. Edge computing and cloud platforms can potentially reduce the processing required for real-time analysis in configurations with restricted resources. By providing a user interface that is easy to understand and straightforward in settings, the technology will be simple to incorporate into farming operations. Without compromising its accuracy or efficiency, it is possible to train the