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Deep learning methods for enhanced stress and pest management in market garden crops: A comprehensive analysis

Mireille Gloria Founmilayo Odounfa [a,*], Charlemagne D.S.J. Gbemavo [a,b], Souand Peace Gloria Tahi [a], Romain L. Glèlè Kakaï [a]

[a] Laboratoire de Biomathématiques et d'Estimations Forestières (LABEF), Faculty of Agronomic Sciences, University of Abomey-Calavi, 04 BP 1525, Cotonou, Benin

[b] Ecole Nationale Supérieure des Biosciences et Biotechnologies Appliquées (ENSBBA), Université Nationale des Sciences, Technologies, Ingénierie et Mathématiques (UNSTIM), BP 14, Dassa-Zoumé, Benin

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ABSTRACT

Various deep learning methods are employed to detect stress and diseases in market garden crops, as well as to assess their severity. This study aims to comprehensively analyze these techniques and identify potential research avenues. The diversity of deep learning techniques was explored through a literature review based on the PRISMA guidelines. Research equations were defined, resulting in a sample of 1,422 publications, of which 72 were deemed usable and considered in the final analysis. For classification tasks, hybrid CNN models were the most widely used (19.2%). Commonly utilized models included VGG16 (10%), InceptionV3 (6.1%), DCNN (5%), and YoloV5 (5%). In object detection tasks, Fast R-CNN was used six times, followed by YoloV5 (three occurrences) and YoloV3 (two occurrences). In segmentation tasks, Mask R-CNN accounted for 28.67% of the models, while DeepLabV3+ accounted for 24.98%. Assessing disease severity in market garden crops is complex due to the unique criteria for each plant disease and the presence of multiple diseases across different crop types. To address this complexity, establishing a standardized method is crucial. Further research is essential to enhance the application of deep learning techniques in the study of market garden crops. This includes gathering extensive datasets that encompass various scenarios of crop diseases and considering the impact of climate variations on stress manifestation.

1. Introduction

A market garden entails the cultivation of vegetables, fruits, and flowers on a small scale for commercial purposes. These fresh produce items are typically sold directly to consumers and restaurants, offering a sustainable, locally sourced option for healthy and vibrant ingredients. Market Garden crops are acrucial part of the global agri-food system, contributing to the daily nutritional needs of millions of people worldwide [26]. However, the growth and optimal health of vegetable plants are often disrupted by stressors, such as disease, pests, and extreme environmental conditions, which can lead to serious yield losses [99,75]. While previous studies have focused on plants in general and have often included fruits and vegetables in their scope of analysis, it is essential to focus exclusively on market gardening crops. Market garden crops are often more susceptible to diseases and pests than other types of plants [46,65], presenting distinct challenges that require specific solutions. Failure to promptly detect and appropriately treat the rapid spread of diseases in these plants can have detrimental consequences, including substantial production losses, declines in market performance, and increased unemployment rates within the food and agriculture sector [94]. The conventional use of chemical pesticides and fungicides to combat these stresses has negatively impacted the environment and human health [64], making it more essential than ever to find sustainable and effective solutions for predicting and managing stresses and pests affecting market garden crops. Additionally, the traditional practice for farmers and agronomists has primarily relied on visual diagnostic methods to identify disease symptoms in plants. This involves visually inspecting leaves, stems, and fruit for signs of stress or disease [99,58]. However, this approach heavily depends on individual expertise, making it prone to errors and subjective judgments. Manual sampling methods involved collecting plant samples in the field for later laboratory analysis. This is time-consuming, does not allow for real-time measurements, which are often crucial for disease management, and is also very expensive [85].

* Corresponding author.
E-mail address: odounfemi1@yahoo.com (M.G.F. Odounfa).

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In this context, precision agriculture is emerging as a promising solution, leveraging cutting-edge technologies and data-driven methodologies to increase agricultural productivity and sustainability [14]. Precision agriculture relies on advanced technologies such as multispectral and hyperspectral sensors, RGB-Depth (RGB-D) cameras, platforms like unmanned aerial vehicles (UAVs) and robots, advanced information systems, such as geographic information systems (GIS) and Internet of Things (IoT), algorithms and machine learning [14]. These technologies allow farmers to better understand their production environment by collecting data on parameters such as soil quality, pest presence, air composition, temperature, and light distribution [21]. The benefits of precision agriculture are manifold, including increased crop productivity and quality, reduced environmental impact of agriculture, and enhanced food security [60]. By combining these advanced technologies with the optimization of the available resources, precision agriculture can contribute to profitable, sustainable, and high-value agricultural production [33,89]. Several tasks, including classification tasks, are carried out using various techniques [54]. However, to achieve classification using conventional machine learning techniques, a series of steps must be followed, including pre-processing, feature extraction, wise feature selection, learning, and classification. Feature selection plays a significant role in determining the performance of these machine learning techniques. In contrast, deep learning (DL), a subset of machine learning, has the advantage of automating the learning of feature sets for various tasks, unlike conventional ML methods. On the other hand, deep learning (DL), a subset of machine learning, has the advantage of automating the learning of feature sets for various tasks, unlike conventional ML methods, and also improves detection speed and

Despite significant progress in deep learning, it is crucial to acknowledge and address the challenges inherent in this field. The first challenge is the need for large amounts of data to train models [9,90,57,70,23]. Another challenge is the complexity and substantial computing power required to train and execute these models [92]. The performance of deep learning models can be influenced by the quality and representativeness of the training data [32]. Deep learning models can occasionally suffer from overfitting to the training data, resulting in limited generalization to new and unseen data. Effectively handling unknown scenarios poses a significant challenge in ensuring the model's adaptability and robustness [90]. This comprehensive understanding serves as a foundation for conducting thorough investigations into the detection and estimation of plant disease severity, thereby facilitating the advancement of research in this critical agricultural domain.

Several journal articles have been published on this subject in recent years. Bondre et al., Hasan et al., and li et al. [16,39,52] presented a comprehensive investigation into deep learning architectures, data sources, and various image processing techniques commonly employed in analyzing leaf imaging data. Ajay Chakravarty et al. [19] highlighted the latest advancements in crop leaf disease diagnosis, focusing on the application of deep learning technology. Their research sheds light on contemporary patterns and challenges associated with detecting plant leaf diseases. David et al. and Krishnamoorthy et al. [22,50] presented a comprehensive analysis of early detection techniques for tomato leaf diseases in India, utilizing a hybrid computer vision-based deep learning architecture. This research aims to enhance disease detection in tomato crops, providing valuable insights into improving agricultural practices in Africa. However, the challenges faced by vegetable crops are unique and require specific approaches to ensure their health, productivity, and sustainability [24].

While many studies have focused on plants in general and fruits and vegetables in particular, it is imperative to recognize the importance of specifically focusing on market garden crops. These crops are often vulnerable to environmental stresses, diseases, and pests, which can lead to significant crop losses, thereby affecting food security, the regional economy, and the environment [86]. Unlike fruit crops, vegetable crops are characterized by a short growth cycle, high diversity, and increased susceptibility to diseases and pests [86].

This study analyzed various deep learning methods for predicting and managing stresses and pests affecting market garden crops. Our goal was to offer valuable insights into technological advancements and optimal practices for detecting and estimating disease and pest severity in vegetable crops. Our contributions in this study are as follows: i) This review is the first to present a comprehensive list of the most commonly used data sources for various tasks related to this field. ii) We provide a comprehensive analysis of deep learning methods specifically applied to the management of stresses and pests in market garden crops. iii) We conduct a detailed examination of the different deep learning models utilized for object detection, classification, and segmentation tasks in images of market garden crop leaves. iiii) We analyze the strategies used to estimate the severity of stress in crops. iiiii) We discuss the significant challenges faced in improving techniques and ensuring food safety in this context.

2. Clarification of concepts

This section outlines the mathematical framework of deep learning and discusses key hyperparameters essential for designing an effective deep learning algorithm.

2.1. Theoretical framework of deep learning

2.1.1. The deep learning

Deep learning is a machine learning approach that leverages deep artificial neural networks to learn complex patterns from raw data. It has the potential to deliver high performance across various domains by harnessing computational power and vast amounts of available data [88].

The architecture of a deep neural network is inspired by the intricate structure of the human brain. It involves organizing artificial neurons into layers, creating an artificial feed-forward neural network [10]. The realization of such a neural network, which refers to the function it provides, is a composition of affine linear mappings and non-linear activation functions denoted as $\rho : \mathbb{R} \rightarrow \mathbb{R}$. To elaborate further, the realization of a neural network with L layers, where N_0, N_L and N_l, (for $l = 1, ..., L-1$) represents the number of neurons in the input layer, output layer, and lth hidden layer, respectively, along with weight matrices, $W^{(l)} \in \mathbb{R}^{N_l \times N_{l-1}}$ and bias vectors $b^l \in \mathbb{R}^{N_l}$, is defined as follows [83]:

$$\Phi(x, \theta) = W^{(L)} \rho(W^{(L-1)} ... \rho(W^{(1)} x + b^{(1)}) + ... + b^{L-1}) + b^L, \qquad x \in \mathbb{R}^{N_0}, \tag{1}$$

with free parameters $\theta = ((W^{(l)}, b^{(l)}))_{l=1}^{L}$. Given training data

$$(\mathcal{Z}^{(i)})_{i=1}^{m} := ((x^{(i)}, y^{(i)}))_{i=1}^{m}, \tag{2}$$

which arise from a function $g : \mathbb{R}^{N_0} \rightarrow \mathbb{R}^{N_L}$, the parameters are the learned by minimizing the empirical risk

$$\mathbf{E}_m(\Phi(., \theta)) = \frac{1}{m} \sum_{i=1}^{m} \mathcal{L}(\Phi(., \theta), \mathcal{Z}^{(i)}), \tag{3}$$

with $\mathcal{L}$ a suitable loss function. In practice, this optimization process is commonly achieved through stochastic gradient descent, a variant of gradient descent that accommodates a large number of parameters and training samples and training samples, which can reach into the millions. The performance of the trained neural network is then evaluated based on its ability to accurately fit a test dataset.

2.1.2. Stochastic gradient descent and hyperparameters

Minimizing the empirical risk $\mathbf{E}m(\Phi(., \theta))$ using gradient descent (GD) has often been proposed ([17]). In each iteration, the parameters θ are updated based on the gradient of $\mathbf{E}_m(\Phi(., \theta))$,

Table 1
Essential hyperparameters for CNN architecture design.

Hyperparameter	Symbol
Convolutional Layer Count	N_c
Kernels per Convolution Layer	$kN_i, i \in N_c$
Convolution Kernel Size	$kS_i, i \in N_c$
Activation Function per Layer	$aF_i, i \in N_c$
Pooling Size per Layer	$pS_i, i \in N_c$
Dense Layer Count	N_d
Layer Connectivity Pattern	$P_i, i \in N_d$
Neurons per Dense Layer	$nN_i, i \in N_d$
Weight Regularization	$R_i, i \in N_d$
Dropout Rate	R_{dropout}
Batch Size	S_{batch}
Learning Rule	L_{rule}
Learning Rate	L_{rate}

$$\theta_{t+1} = \theta_t - \gamma \frac{1}{m} \sum_{i=1}^{m} \nabla_\theta \mathcal{L}(\Phi(.,\theta), \mathcal{Z}^{(i)}), \tag{4}$$

where γ is an appropriately chosen learning rate. The stochastic gradient descent (SGD) algorithm is significantly simplification. Instead of computing the gradient of $\mathbf{E}_m(\Phi(.,\theta))$ exactly, each iteration estimates this gradient based on a randomly selected example $(\mathcal{Z}^{(i)})_{i=1}^m$. The new update is given by,

$$\theta_{t+1} = \theta_t - \gamma \frac{1}{m} \nabla_\theta \mathcal{L}(\Phi(.,\theta), \mathcal{Z}^{(i)}). \tag{5}$$

The Stochastic Gradient Descent (SGD) is a key optimization method in deep learning that addresses challenges in optimizing deep neural networks [37]. Unlike traditional gradient descent, the Stochastic Gradient Descent (SGD) calculates gradients on random mini-batches of the dataset, offering benefits such as computational efficiency by reducing the time needed to estimate gradients, adaptability by introducing noise to avoid local minima and efficient handling of massive datasets [37]. The significance of the learning rate cannot be overstated in the context of stochastic gradient descent (SGD). It serves as a pivotal hyperparameter, determining the step size of each parameter update step. The selection of an appropriate learning rate is a fundamental prerequisite to ensure efficient model convergence [49]. Various approaches exist to address the task of learning rate selection. These span from opting for a predetermined, static learning rate through manual calibration to the utilization of adaptive learning rate techniques, including Adaptive Gradient Algorithm (AdaGrad), Root Mean Squared Propagation (RMSProp), and Adaptive Moment Estimation (Adam) [25]. These adaptive methodologies automatically fine-tune the learning rate grounded on gradient information, thereby mitigating the necessity for manual adjustments. In summary, SGD is a fundamental technique for training deep neural networks, and its combination with precise hyperparameter management is vital to ensure the success of deep learning. Table 1 presents essential hyperparameters for designing CNN architectures, including parameters related to convolutional layers, dense layers, weight regularization, dropout rate, batch size, learning rule, and learning rate.

2.1.3. Multimodal deep learning

Multimodal Deep Learning constitutes a branch within deep learning focusing on amalgamating and interpreting data from diverse modalities, including text, images, audio, video, and sensor data [63]. By harnessing the collective strengths of these modalities, Multimodal Deep Learning endeavors to construct a holistic data representation, thereby enhancing performance across a spectrum of machine learning tasks [12].

Typically, multimodal architectures are organized with three core components, as illustrated in Fig. 1 components [100]:

1. Unimodal Encoders: These encoders are responsible for processing and encoding each input modality separately, usually employing a dedicated encoder for each modality.
2. Fusion Network: This network integrates the features extracted from each modality during the encoding process, combining them into a unified representation.
3. Classifier: The classifier takes the fused data and makes predictions based on the integrated features.

3. Materials and methods

Following the systematic review process outlined in a previous study [7], this review undertakes a comprehensive approach to establish research questions, identify relevant sources, define selection criteria, and develop quality assessment procedures. During the implementation phase, research articles were selected based on specific keywords from pertinent academic databases. The synthesis stage involves a critical analysis of existing techniques, evaluating their strengths and weaknesses, and determining their suitability for practical application in the field.

3.1. Searching approach

A literature search was conducted on deep learning methods for enhanced stress and pest management in market garden crops from major databases, including Google Scholar, Scinapse, Semantic Scholar, ProQuest, Scopus, Web of Science. The search employed the following keywords: “vegetable diseases” OR “vegetable pests” OR “vegetable biotic stress” OR “vegetable abiotic stress” OR “severity estimation” OR “smart agriculture” OR “precision agriculture”, combined with “deep learning” OR “neural networks” OR “machine learning” OR “transfer learning” OR “segmentation” OR “classification” OR “fine-tuning”. Subsequently, articles were selected or excluded based on predefined criteria detailed in Table 2.

3.2. Selection and extraction of articles

Articles not originally written in English or lacking essential information were excluded. Initially, a pool of 1422 research articles comprising journal articles, conference papers, and book chapters was identified, from which 421 duplicates were removed. The selection process rigorously examined titles, abstracts, and full article content to ensure relevance to the application of Deep Learning (DL) for detecting stress and estimating disease severity in market garden crops. Further scrutiny of titles and abstracts led to the exclusion of 510 additional articles. Among these, 109 were inaccessible due to unavailable full texts, 255 were identified as literature reviews, and 146 were categorized as book reviews, editorials, conference abstracts, or seminar papers. Following these screening steps, 491 articles remained in the subset. Of these, 309 were found irrelevant as they employed artificial intelligence methods other than Deep Learning. Among the remaining 182 articles, 110 focused on stress in species other than vegetable crops and were subsequently excluded from the final selection. A thorough examination of references cited in systematic reviews, books, and related articles was conducted before identifying 72 articles published between 2017 (The concept of assessing plant disease severity through deep learning models was initially introduced in 2017 by Wang et al. [97,27]) and May 2023. Fig. 2 provides an overview of the article screening and filtering process based on PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [69].

3.3. Research questions

To structure the results of this literature review effectively, we formulated ten research questions focused on specific objectives:

RQ1: In which country were the studies conducted?
This question aims to identify geographical variations that may impact research outcomes.

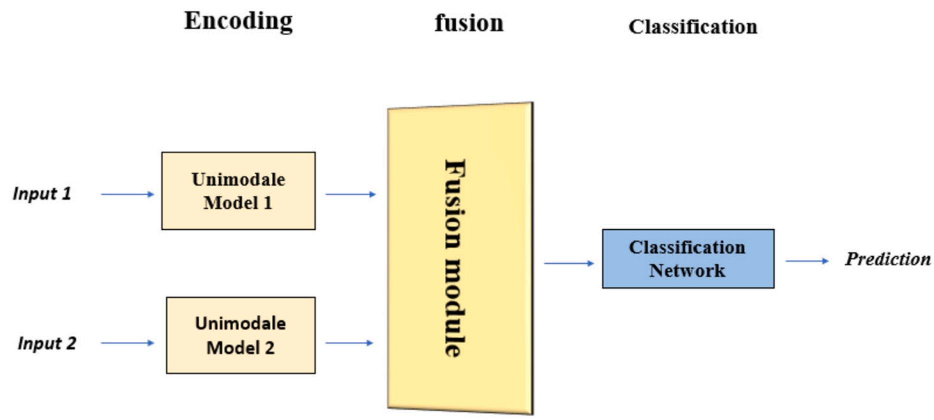

Fig. 1. General multimodal workflow integrating two independent unimodal neural networks.

Table 2
Selection criteria.

Considered studies	Unconsidered studies
Employed deep learning techniques	Other languages than English
Articles published between 2017 and May 2023	Short memos
Studies focusing on severity estimation	Inaccessibility of full-text articles
Studies focusing on crop disease detection	Studies not related to market garden crops

RQ2: Which vegetable species were studied?
This question provides insights into the specific focus of the research.
RQ3: What types of data and sources were utilized?
This inquiry explores the variety and origins of data employed in the reviewed studies.
RQ4: What deep learning techniques were employed for identifying vegetable crop diseases and pests?
This question seeks to recommend optimal deep learning methods for improving prevention, detection, and management strategies.
RQ5; What are the objectives behind using multimodal Deep Learning techniques?
This question investigates the application of advanced technologies to address agricultural challenges and foster innovation.
RQ6: What are the primary evaluation criteria for assessing the effectiveness of disease and pest detection systems, as well as severity estimation?
This explores the metrics used to gauge the reliability and relevance of study outcomes.
RQ7: What are the most effective classification models?
This analysis provides insights into the strengths and weaknesses of different models for specific applications.
RQ8: How was the severity of diseases assessed?
This question delves into the methodologies used to evaluate disease severity and their outcomes.
RQ9: What techniques are effective in improving model performance and mitigating overfitting?
This explores strategies such as regularization, data augmentation, and cross-validation to enhance model robustness.
RQ10: What are the weaknesses of current approaches and authors' perspectives?
This question identifies limitations in existing studies and suggests directions for future research.

3.4. Data analyse

Addressing the objectives of this study, we evaluated various aspects to assess the effectiveness of severity detection and estimation systems in vegetable crops. First, we conducted a bibliometric analysis of the keywords (4.1) using VOSviewer [18]. Next, we examined the global distribution of studies (4.2), the types and sources of data utilized (4.3), specific plant species studied (4.4), deep learning techniques for disease and pest identification (4.5), the rationale behind using multimodal Deep Learning techniques (4.6), the primary evaluation criteria (4.7), best classification models (4.8), methods for assessing disease severity (4.9), and strategies to enhance model performance and mitigate overfitting (4.10). Graphical statistics were generated using Python software in the Jupiter interface, leveraging libraries such as NumPy, Pandas, Matplotlib, and Seaborn, as well as R software utilizing the ggplot function from the package 'ggplot2'. Finally, this comprehensive approach enabled us to offer pertinent recommendations (4.11) to strengthen prevention, detection, and management strategies for market gardening, while identifying potential avenues for further advancement in this dynamic field.

4. Results and discussion

4.1. Bibliometric analysis of keywords

Examining keywords related to deep learning methods to improve stress and pest management in vegetable crops reveals significant trends that underscore advances in agricultural artificial intelligence, that underscore shift from traditional machine learning techniques to more sophisticated deep learning methodologies (Fig. 3). The pervasive use of deep learning methodologies (36 occurrences) underscores a data-driven approach aimed at developing more accurate and effective solutions for stress and pest management. Convolutional neural networks (CNNs) are prominently emerging (32 occurrences), highlighting their pivotal role in image processing and disease detection in vegetable crops (Table 3). Additionally, the presence of Conditional Generative Adversarial Networks (CGANs) signifies the application of innovative techniques for generating synthetic images and targeted solutions. Transfer learning is widely employed (13 occurrences), underscoring its utility in adapting pre-existing models to tackle specific agricultural challenges. Keywords related to multimodal fusion (Fig. 3) indicate a focus on precisely delineating cropped regions and integrating diverse data sources to enhance model robustness. Additionally, the inclusion of precision agriculture (Fig. 3) emphasizes efforts to optimize resource utilization and increase agricultural productivity while minimizing environmental impact. Overall, these findings reflect a concerted effort to harness advanced technologies and interdisciplinary approaches to address the intricate challenges confronting modern agriculture.

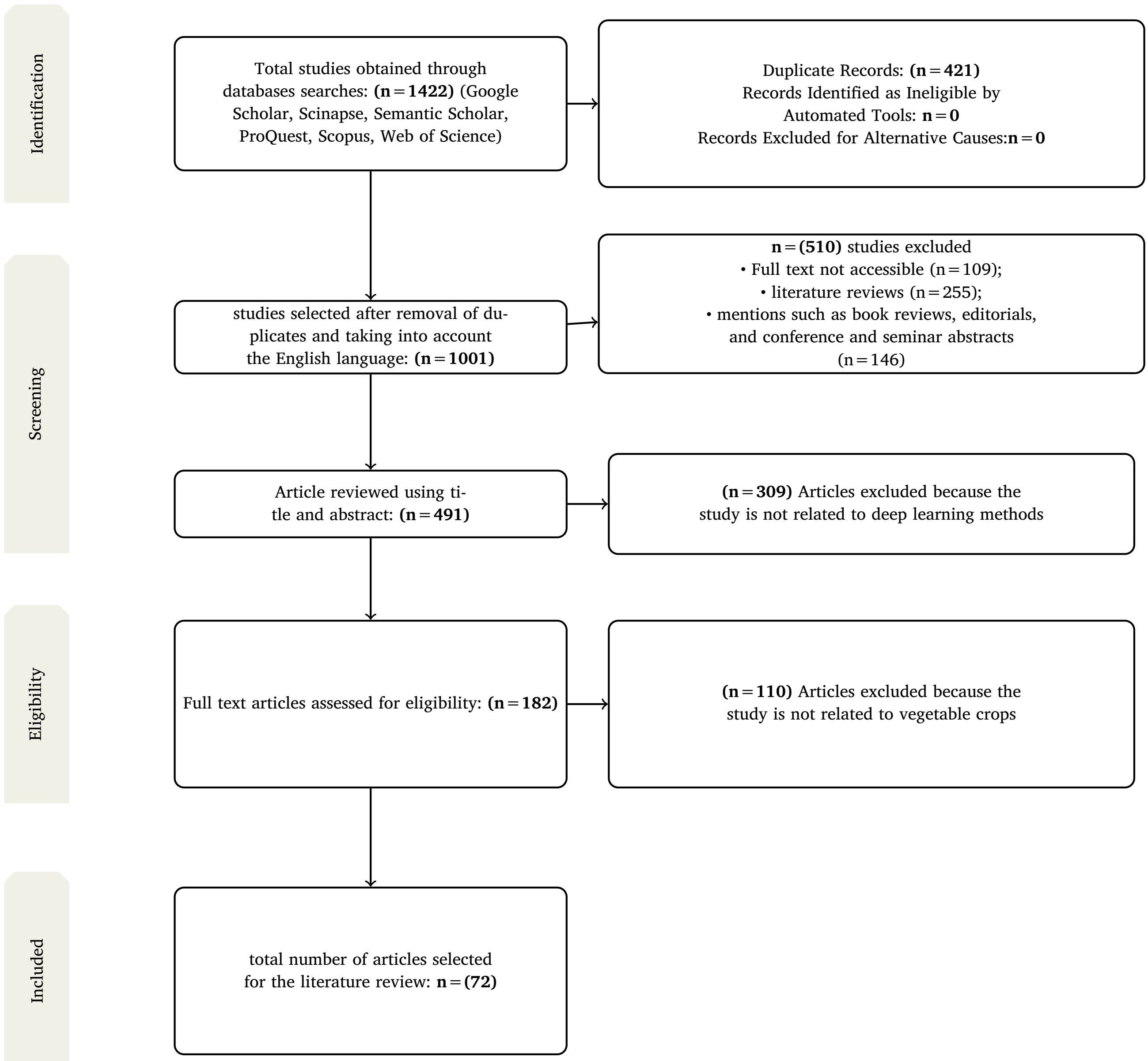

Fig. 2. PRISMA Flow Diagram depicting the selection process of the 72 studies included in the systematic review.

Table 3
Top 15 keywords that appear most frequently in the analyzed papers.

Keyword	Occurrences	Total Link Strength
Deep Learning	36	155
CNN	32	135
Transfer Learning	13	57
Plant disease	10	48
Object detection	8	32
AI	7	28
Segmentation	6	23
Chlorophyll content	5	24
Cucumber disease	5	20
CGAN	4	23
Data augmentation	4	22
Image recognition	4	22
Agriculture	4	21
Disease severity	4	20
Tomato plant disease	4	19

4.2. In which country were the study conducted?

The analysis of the collected data for this literature review, which focuses on the application of various deep learning methods in predicting and managing stresses and pests affecting vegetable crops, reveals a broad geographic distribution of studies. Asian countries, particularly India (27.27%), China (19.70%), and Indonesia (1.52%), emerge prominently with substantial research activity, reflecting the agricultural significance of the region. Africa and Europe also make significant contributions, whereas South America, North America, and Oceania show comparatively lower representation. This distribution underscores the global reach of agricultural challenges addressed by deep learning methods highlights opportunities for international collaboration in tackling these challenges comprehensively [96]. Before delving into the detailed analysis, let us first observe the expansive landscape of global research as depicted in Fig. 4.

The graph in Fig. 5, illustrating the evolution of the years of publication of research articles, reveals an interesting trend. The analysis of this figure shows a growing interest in research work on the aspects targeted

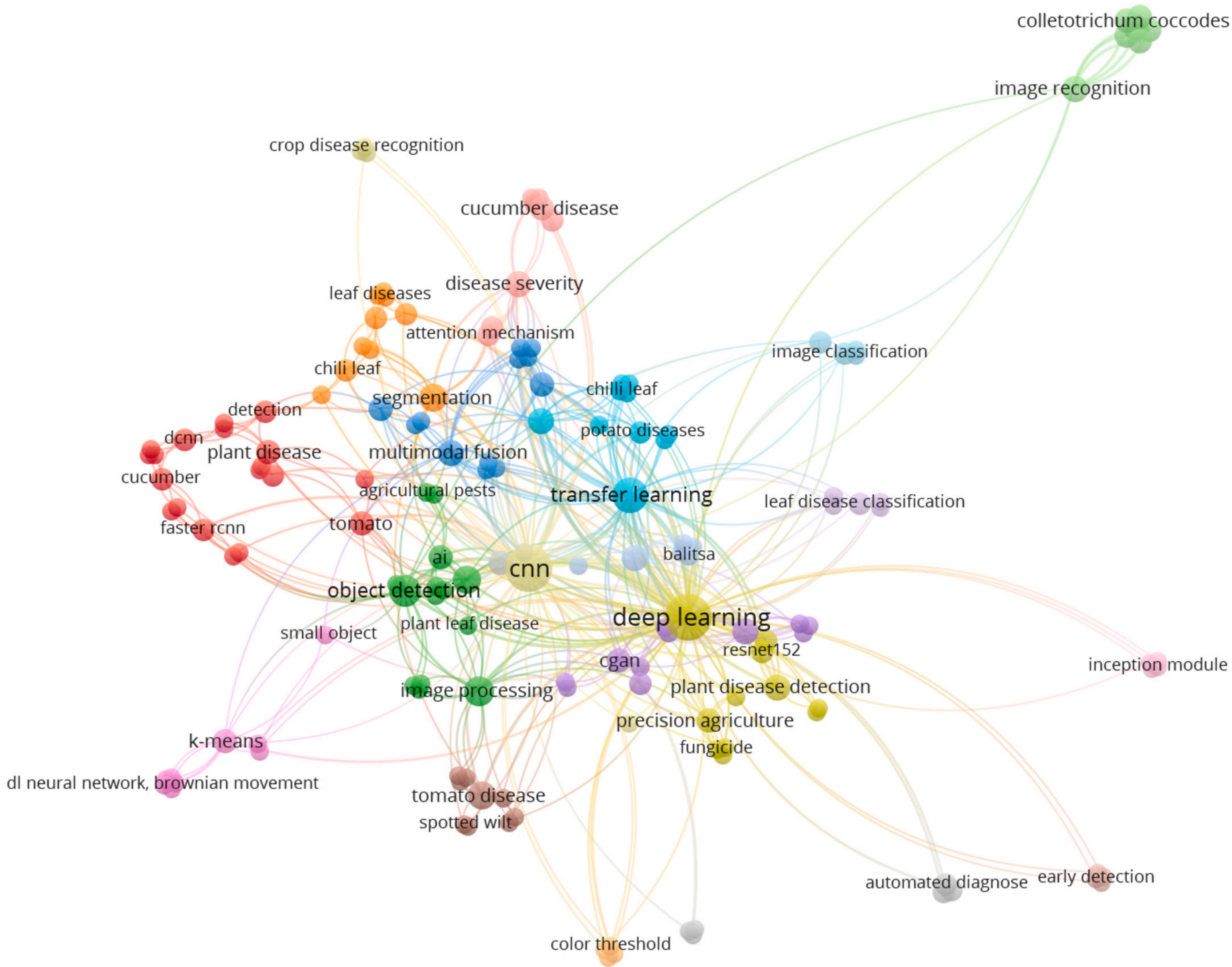

Fig. 3. Cluster map of keywords.

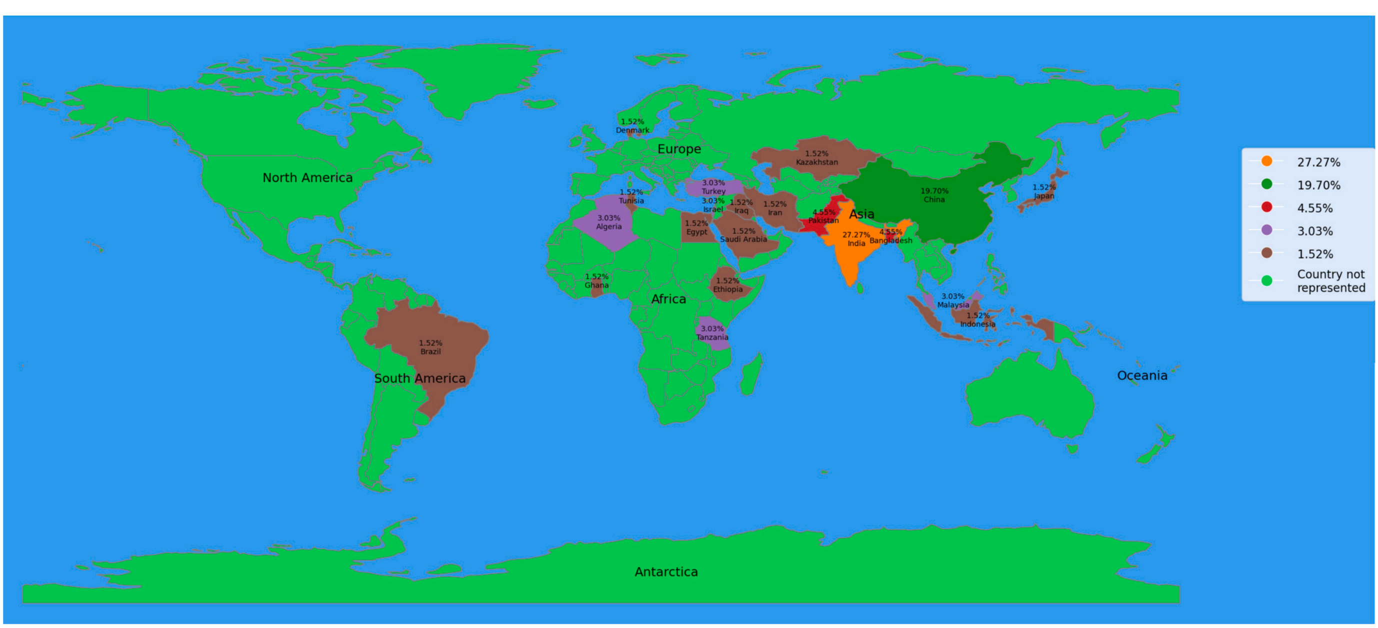

Fig. 4. Geographical distribution of the reviewed studies.

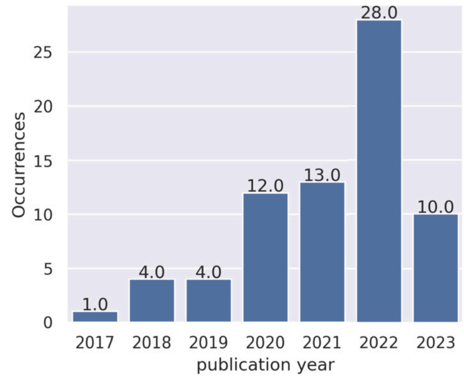

Fig. 5. Distribution of publication years for a total of 72 papers.

over the study period (2017–2023), with a majority of recent papers (the year 2022, with 28 papers out of 72 in total). We obtained a total of 10 papers for the year 2023 since data collection ended in May 2023. These findings underscore the critical importance of research in this field for agriculture and food security, highlighting researchers' commitment to addressing these escalating challenges.

4.3. What types of data and sources were utilized?

Deep learning relies on large and diverse datasets to effectively train models. The primary dataset consists predominantly of images (92%), with supplementary data types including climatic variables such as mean temperature, rainfall, humidity, wind speed, sunlight, and solar radiation (8%).

Analysis of the image data sources used in the 72 articles included in this study reveals significant diversity in terms of data origins, but also raises critical questions regarding reliability, representativeness, and potential bias. The use of field data is predominant (53%). While crucial for a contextual understanding of issues, this data may also be subject to collection bias based on geographic location, season, and specific agricultural practices. Additionally, the lack of standardized collection protocols could introduce inconsistencies in the data, impacting the validity of the conclusions. After the primary databases, the public data source "PlantVillage" appears as the most frequently mentioned, with a percentage of (22.6%). This importance can be attributed to its specialization in detecting plant diseases and pests. However, overreliance on this source could introduce selection bias, as data could be more available for some species than others, which would bias the results and neglect species less represented on the platform. Next, we have online resources such as "GitHub" and "Kaggle"(8.7%), illustrating their usefulness for accessing pre-annotated datasets. However, government databases such as "Food Inspection Agency (CFIA)" and "United States Department of Agriculture (USDA)" are also exploited with a percentage of 3.5%, which highlights their role in agricultural research. However, their limited use could be due to constraints linked to data availability or the restricted geographical scope of some of these sources.

In summary, the analysis of data sources underscores the need for a balanced approach to information collection, considering each source's advantages and limitations. Diversification of sources is crucial to mitigate potential biases and ensure the validity and representativeness of results. Awareness of the limitations and challenges associated with each source is crucial for critically interpreting findings in studies focused on predicting and managing stress and pests in vegetable crops.

4.4. Which vegetable species were studied?

In this review, the selected documents encompassed 13 distinct market garden crop species, namely: tomato (*Solanum lycopersicum L.*), potato (*Solanum tuberosum L.*), cucumber (*Cucumis sativus L.*), pepper (*Capsicum annuum L.*), mustard (*Brassica nigra L.*), Zingiberaceae (*Curcuma longa L.*), kenaf (*Hibiscus cannabinus L.*), Sponge gourd (*Luffa cylindrica L.*), mung bean (*Vigna radiata L.*), Okra (*Abelmoschus esculentus L.*), lettuce (*Lactuca sativa L.*), cabbage (*Brassica oleracea L.*), carrot (*Daucus carota L.*). Among these species, tomato (43 occurrences) emerges as the most extensively studied, highlighting its susceptibility to stress and pest-related challenges (Fig. 6). This prominence can be attributed to its economic significance and widespread cultivation [38]. Other noteworthy species include potato (12 occurrences), pepper (7 occurrences), and cucumber (5 occurrences). The species' diversity showcases a comprehensive approach to addressing various agricultural challenges. However, the apparent emphasis on certain species, such as tomato and potato, likely stems from their global economic importance and vulnerability to a wide array of stresses and pests [15,31]. Additionally, the inclusion of less common species underscores efforts to broaden research horizons and explore lesser-known crops. Nevertheless, there remains potential for further diversification, as some crops are represented only once or twice in the dataset, indicating opportunities for expanded investigation.

Overall, while the focus on extensively cultivated crops such as tomatoes and potatoes is justified, broadening research efforts to encompass a wider variety of vegetables would enhance the comprehensiveness and applicability of stress and pest management strategies in the agricultural sector. This approach has the potential to foster more resilient agricultural practices and bolster global food security.

4.5. What deep learning techniques were employed for identifying vegetable crop diseases and pests?

The application of deep learning methodologies in plant disease detection and severity estimation has introduced a wide array of advanced architectures and techniques. These methodologies encompass segmentation, classification, and object detection among other categories. The insights derived from these diverse approaches offer promising perspectives on deep learning's potential to tackle the complex challenges associated with monitoring crops, identifying diseases, and managing pests. Within this comprehensive review, we meticulously delve into a spectrum of models and architectures, including but not limited to Visual Geometry Group (VGG), Residual Networks (ResNet), Mobile Networks (MobileNet), You Only Live Once (YOLO), Faster region-based convolution neural network (Faster R-CNN), and DeepLabV3+. Each of these architectures has been carefully tailored to meet the specific requirements of disease detection and severity estimation in vegetable crops. However, it is essential to acknowledge that their effectiveness can vary in terms of accuracy, speed of execution, and adaptability to different datasets. This comprehensive review offers an all-encompassing overview of the prevailing landscape of deep learning methodologies employed in the domain of disease detection and estimation within the context of vegetable crops. In doing so, it lays the groundwork for illuminating novel insights and fostering ongoing enhancements in this pivotal arena of contemporary agricultural research.

Deep learning has gained significant traction in agricultural applications, particularly in tasks such as identifying plant diseases and pests and estimating their severity. A commonly employed method is deep learning-based image classification, which typically involves supervised training using labeled image datasets to classify objects accurately. This process is facilitated by utilizing the softmax activation function in the final output layer. The efficacy of image classification models in identifying plant diseases has proven remarkable across various crops and environmental conditions.

4.5.1. Image classification

In this review, 32% of the authors introduced their own neural network models. For example, Soumia et al. [13] proposed a rapid approach using a low-complexity convolutional neural network (CNN). Their study demonstrated impressive results, achieving an accuracy rate

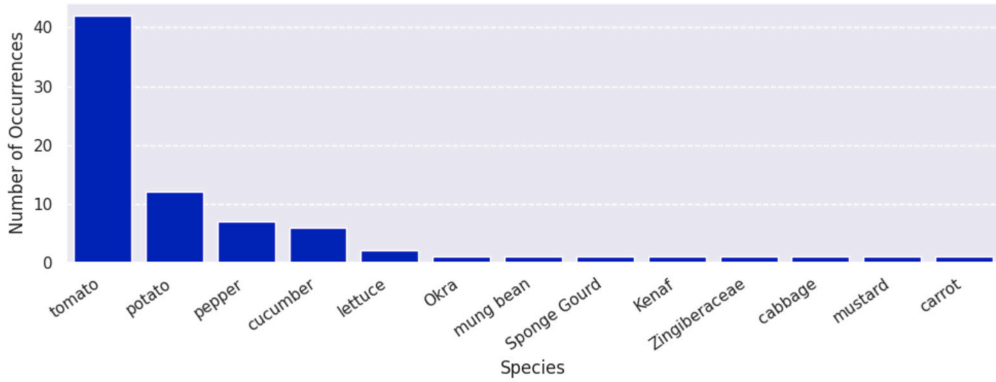

Fig. 6. Distribution of species examined.

of 97.04% in disease classification and an error rate of less than 0.2. These findings confirm the effectiveness of their model in accurately distinguishing between various diseases in tomato cultivation. Similarly, Birhanu et al. [30], Yaser et al. [45], and Vikas et al. [80] have proposed CNN architectures for the classification of tomato diseases. Gnanave et al. [78] presented an approach for detecting and classifying tomato leaf diseases using a Convolutional Neural Network (CNN) on a dataset of 3000 images from PlantVillage. Their CNN model, comprising two convolutional layers and two pooling layers, outperformed pre-trained models such as InceptionV3, ResNet 152, and VGG19. Experimental results showed a training accuracy of 98% and a testing accuracy of 88.17%, underscoring its effectiveness in accurate disease detection. Dor et al. [66] introduced a potato disease classification algorithm using convolutional neural networks (CNNs) to identify four different diseases based on their distinct visual symptoms. The database includes images of varied potato tubers, manually sorted and labeled, and CNN models trained on different splits exhibit high precision in disease classification, achieving an accuracy of 95.85%. Similarly, Trishita et al. [2] and Junfeng Gao et al. [29] have proposed CNN architectures for classifying potato diseases. Rishabh et al. [81] proposed a multiple classification model using a deep learning (DL) approach. The model, based on a convolutional neural network (CNN), categorizes 1500 images collected from mustard crops, distinguishing between healthy and downy mildew-infected (MDM) images while considering the severity levels of the MDM. The multi-classification achieved an accuracy of 96.66%. These proposed models show a willingness to adapt the architectures to the specific needs of disease detection.

Several authors employed classic models, while others utilized enhanced versions. Of the 72 studies considered, 24 used classification models such as DenseNet121, SqueezeNet, InceptionV2, ResNetV2, ResNet101, MobileNetV2, ResNet18, VGG16, VGG19, AlexNet, InceptionV3, EfficientNetB3, MobileNetV3, and DenseNet169. Abbas et al. [1] employed Conditional Generative Adversarial Networks (C-GAN) to synthesize tomato leaf images and trained a DenseNet121 model through transfer learning. Their method achieved impressive accuracies of 99.51%, 98.65%, and 97.11% for classifying tomato leaf images into 5, 7, and 10 disease categories, respectively, highlighting the robustness of DenseNet121 compared to VGG19, ResNet50, Inception-V3, Xception, and MobileNet.

Fig. 7 illustrates the percentage frequency of neural network architectures used in agricultural research for the classification of diseases and pests of vegetable crops. Each bar represents a specific architecture, and its height corresponds to the number of times that architecture was mentioned in the studies reviewed. Hybrid CNN (19.2%), VGG16 (10%), InceptionV3 (6.1%), DCNN (5%), and YoloV5 (5%) are the most used classification models. This visualization provides valuable insights into the popularity and use of different neural network models to address agricultural challenges related to disease identification and severity estimation.

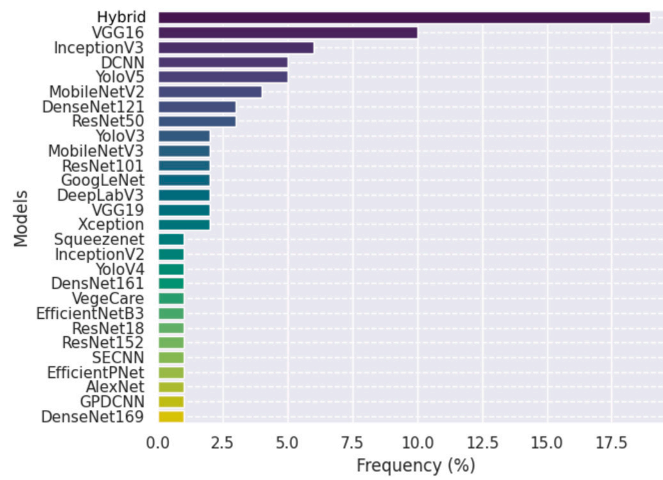

Fig. 7. Deep learning models used for classification.

While image classification remains a prevalent deep learning approach in research, its effectiveness in accurately pinpointing the location of pathological lesions in images and simultaneously identifying multiple diseases is limited. Object detection methods have addressed this challenge by enabling precise localization of lesions and the identification of multiple diseases within a single image.

Object detection involves identifying and localizing multiple object instances in images and videos. Our focus here is on deep learning-driven object detection, which relies on supervised training with annotated bounding boxes on provided images. Well-known algorithms in this domain include R-CNN [35], Fast R-CNN [34], Faster R-CNN [74], YOLO [73], and Single Shot MultiBox Detector (SSD) [55]. In the context of research, object detection has been applied to identify plant diseases. Some studies aim to recognize entire diseased leaves, while others focus on pinpointing specific disease lesions.

4.5.2. *Object detection*

Among the studies reviewed, ten employed object detection techniques to identify and localize plant diseases. Kaiyu Li et al. [51] proposed an enhanced algorithm for vegetable disease detection based on YOLOv5s. They evaluated 1000 images representing five diseases and achieved a mean Average Precision (mAP) of 93.1%, effectively reducing missed detections and false positives caused by complex backgrounds. Compared to Nanodet-Plus, YOLOv4-Tiny, and YOLOX-S, their algorithm demonstrated superior detection accuracy and localization precision. Similarly, Mehmet et al. [68] utilized the Faster R-CNN model to analyze 175 images of cucumber leaves affected by mildew disease. Their tests achieved an overall classification accuracy rate of 94.86%. Fig. 8 illustrates the distribution of deep learning algorithms used in this review. Faster RCNN (6 occurrences), YoloV5 (3 occurrences), and

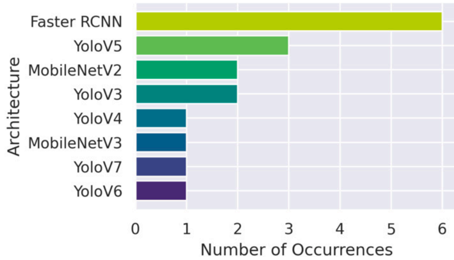

Fig. 8. Deep learning models used for object détection.

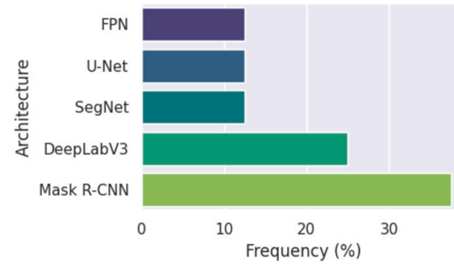

Fig. 9. Deep learning models used for semantic segmentation.

YoloV3 (2 occurrences) were the most frequently employed models for object detection tasks.

Utilizing deep learning-driven object detection holds significant promise in the domain of plant disease identification, enabling simultaneous recognition of various instances of plant diseases within images and videos [79]. Consequently, these methodologies prove highly valuable in dynamic, real-time systems. However, the detection process often results in bounding boxes that encompass surplus information, leading to instances where more extensive content is included than is strictly necessary. For instance, if a disease lesion is positioned diagonally in the frame, the bounding box might encompass additional leaf areas devoid of any disease manifestation. In contrast to conventional object detection methods utilizing bounding boxes, segmentation offers a pixel-level understanding of object boundaries. In the context of plant disease identification, segmentation techniques accurately delineate the extent of disease lesions, ensuring that only relevant areas are considered regardless of their shape or orientation. This detailed approach mitigates the issue of unnecessary encompassing areas observed with diagonal disease lesions in traditional object detection methods. Essentially, segmentation enhances the precision and specificity of object localization. Semantic segmentation through deep learning is another widely adopted methodology for identifying plant diseases. This approach involves training models to segment entire objects within images, assigning a distinct class to every pixel based on training labels. Popular segmentation algorithms such as Mask R-CNN, U-Net, DeepLab, and ENet are frequently used in this context. Supervised training of segmentation models requires ground truth information, with annotations tailored to segmentation offering higher precision as they accurately delineate object shapes compared to bounding boxes. However, it's important to note that creating annotations for segmentation is more time-consuming, thereby increasing labor costs. Commonly used annotation tools for image segmentation include MATLAB and LabelMe.

4.5.3. Segmentation

Fig. 9 illustrates the prevalent adoption of various semantic segmentation architectures in agricultural research. Mask R-CNN (38%) and DeepLabV3 (25%) emerge as the most utilized deep learning models for semantic segmentation tasks. For instance, Qimei et al. [98] employed deep convolutional neural networks and object detection models—specifically Faster R-CNN for disease identification and Mask R-CNN for precise segmentation of infected areas. Their approach effectively identifies multiple types of tomato diseases while accurately delineating the corresponding infected regions. In another study focusing on pest symptoms captured in the field, multi-class semantic segmentation was conducted using three models and four backbone architectures [20]. U-Net with Inceptionv3 proved optimal for segmentation tasks, whereas FPN with ResNet34 and DenseNet121 excelled in severity estimation. This research highlights the computational models' capability to handle complex field images under challenging lighting conditions. Furthermore, Prabhjot et al. [47] utilized Mask R-CNN for tomato segmentation, while Junfeng Gao et al. [29] applied SegNet for precise segmentation of potato late blight lesions. Chunshan et al. [95] proposed a two-stage model (DUNet) integrating DeepLabV3+ and U-Net for cucumber leaf disease severity classification in intricate backgrounds. Their model successfully segments leaves and disease spots with high accuracy.

4.6. What are the objectives behind using multimodal deep learning techniques?

Considering the findings from various research papers, the integration of multimodal deep learning techniques emerges as pivotal for advancing disease identification and classification. By amalgamating data from diverse sources, such as images of diseased plants, environmental parameters like temperature and humidity, and expert knowledge, this comprehensive approach enhances the accuracy and efficiency of disease diagnosis [6]. Ultimately, these advancements contribute significantly to agricultural production by mitigating economic losses and refining crop management practices.

In this study, only 4.5% of the research utilized data of different types. For instance, Ning Zhang et al. [101] developed a disease recognition algorithm employing multimodal deep learning feature fusion via a Multi-ResNet34 convolutional neural network model. Their dataset, comprising images depicting six types of tomato diseases, underwent preprocessing involving image segmentation and data augmentation techniques. This preprocessing notably improved image recognition efficiency and enhanced disease diagnosis accuracy, achieving a remarkable classification accuracy of 98.9% for identifying the six tomato diseases using the enhanced Multi-ResNet34 model. This accuracy surpasses that of a single image recognition model by 1.1 percentage points, underscoring the effectiveness of feature fusion in enhancing disease diagnosis accuracy, particularly in greenhouse crop diseases.

Moreover, the study conducted comparative experiments to validate the superiority of feature fusion through different fusion positions, establishing ResNet34 decision fusion and Multi-ResNet34 as two viable schemes. These findings underscore the efficacy of employing multimodal fusion deep learning techniques for disease identification in agricultural contexts.

4.7. What are the primary evaluation criteria for assessing the effectiveness of disease and pest detection systems, as well as severity estimation?

We present here a comprehensive range of fundamental evaluation measures utilized in the 72 studies, offering nuanced insights into the quality of deep learning models employed.

Specifically, we define the following terms:

True Positive (TP): Number of samples correctly identified as belonging to class C by the classifier.

True Negative (TN): Number of samples correctly identified as not belonging to class C.

False Positives (FP): Instances incorrectly classified as class C when they do not belong to it.

False Negatives (FN): Number of samples that should have been classified as class C but were categorized into a different class.

- **Accuracy**: Accuracy measures the proportion of correct predictions among all predictions: [43]:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TN} + \text{TP} + \text{FN} + \text{FP}}. \tag{6}$$

- **Precision**: Precision measures the proportion of true positive predictions among all positive predictions made: [53]:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}. \tag{7}$$

- **Recall**: Recall measures the proportion of true positive samples correctly predicted among all actual positive samples [54]:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \tag{8}$$

- **F1-Score**: F1-score is the harmonic mean between precision and recall. It combines both measures for a more balanced evaluation [1,48]:

$$\text{F1-Score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}}. \tag{9}$$

- **Confusion Matrix**: A matrix summarizing classification results by showing true positives, true negatives, false positives, and false negatives [45]:

$$\begin{bmatrix} \text{TP} & \text{FP} \\ \text{FN} & \text{TN} \end{bmatrix}. \tag{10}$$

- **Sensitivity**: Measures the model's ability to identify positive samples correctly [68]:

$$\text{Sensitivity} = \text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \tag{11}$$

- **Specificity**: Measures the model's ability to identify negative samples correctly [68]:

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}. \tag{12}$$

- **Average Precision (AP)**: Average Precision is commonly used to evaluate object detection and information retrieval tasks. To begin, let's introduce the precision-recall (PR) curve. This curve makes it possible to visualize and understand the trade-off between accuracy and the ability to detect positive cases of a classifier.
The recall is represented on the horizontal axis of the PR curve. Precision is represented on the vertical axis of the PR curve.
The PR curve is constructed by varying the decision threshold of the classifier, which is the threshold at which a prediction is considered positive or negative. The corresponding recall and precision are calculated at each threshold, and a point is plotted on the PR graph. By connecting these points, the PR curve is obtained.
The area under the PR curve (AP) gauges the model's overall performance in terms of the trade-off between precision and recall. A high AP value indicates that the model achieves both high precision and good recall, which is generally desirable. In other words, AP measures the "hunt for true positives" (high recall) while minimizing errors (false positives) [11]:
- For continuous PR curves:

$$AP = \int_0^1 PR(r)\,dr. \tag{13}$$

- For discrete PR curves:

$$AP = \sum_{k=1}^{n} P_k \cdot r_k. \tag{14}$$

- **mAP (Mean Average Precision)**: Mainly used to evaluate object detection model performance. Average of individual Average Precisions (AP) calculated for each class [53]:

$$\text{mAP} = \frac{\text{AP}_1 + \text{AP}_2 + \ldots + \text{AP}_n}{n}. \tag{15}$$

- **IoU (Intersection over Union)**: Used to evaluate object detection accuracy by comparing the overlap between prediction and ground truth areas. The formula is given by [28]:

$$\text{IoU} = \frac{\text{Area of Intersection}}{\text{Area of Union}}. \tag{16}$$

- **Dice Coefficient**: The Dice coefficient serves as a metric for assessing the similarity between a predicted segmentation and its associated ground truth by quantifying the extent of overlap between the two. It is calculated as twice the shared region's area divided by the combined total number of pixels in both images [104]:

$$Dice = \frac{2 \cdot |X \cap Y|}{|X| + |Y|}, \tag{17}$$

where X is the predicted set of pixels and Y is the ground truth.
- **MIoU (Mean Intersection over Union)**: The mean Intersection over Union (mIoU) is a metric used to evaluate the effectiveness of image segmentation models by quantifying the level of agreement between predicted segmentation and ground truth regions. Its computation involves averaging the Intersection over Union (IoU) scores for each class, and a higher mIoU value reflects improved segmentation accuracy [103,87]:

$$\text{MIoU} = \frac{1}{\text{Number of Classes}} \sum_{i=1}^{\text{Number of Classes}} IoU_i. \tag{18}$$

- **FWIoU (Frequency-Weighted Intersection over Union)**: FWIoU is determined by computing the average IoU scores for individual classes, with the weights assigned according to the prevalence of each class in the dataset. This method addresses the class imbalance challenge, which arises when a particular class, such as the background class, is prominent in most dataset images. FWIoU is employed in semantic segmentation tasks to assess the performance of segmentation models. It offers a more comprehensive evaluation of the model's ability to accurately segment various classes, considering the frequency distribution of these classes within the dataset. The FWIoU is computed by dividing the sum of the products of the IoU scores and class frequencies by the sum of the class frequencies. This formula can be written as follows [87]:

$$FWIoU = \frac{\sum_{i=1}^{N} IoU_i \cdot f_i}{\sum_{i=1}^{N} f_i}, \tag{19}$$

Where: N is the number of classes, IoU_i is the IoU score for class i, f_i is the frequency of class i in the dataset.
- **MCC (Matthews Correlation Coefficient)**: Measures the quality of binary classification [4].

$$\text{MCC} = \frac{\text{TP} \times \text{TN} - \text{FP} \times \text{FN}}{\sqrt{(\text{TP} + \text{FP}) \times (\text{TP} + \text{FN}) \times (\text{TN} + \text{FP}) \times (\text{TN} + \text{FN})}}. \tag{20}$$

- **severity estimation**: The accuracy of severity estimation is evaluated using the coefficient of determination (R^2) and the Root Mean Square Error (RMSE) [51]. These metrics provide a quantitative measure of how well the severity estimation model predicts the actual severity values. A higher R^2 value indicates a stronger correlation between the predicted and actual severity values, while a lower RMSE value indicates a smaller average difference between the predicted and actual severity values. By optimizing these metrics, we can improve the accuracy of the severity estimation.

The commonly employed metrics for assessing model performance include accuracy (47 occurrences), precision (37 occurrences), recall (30 occurrences), and F1 score (26 occurrences) (Fig. 10).

4.8. *What are the most effective classification models?*

Table 4 provides a summary of relevant articles with comparative studies, which we searched for this analysis. Each article is listed with

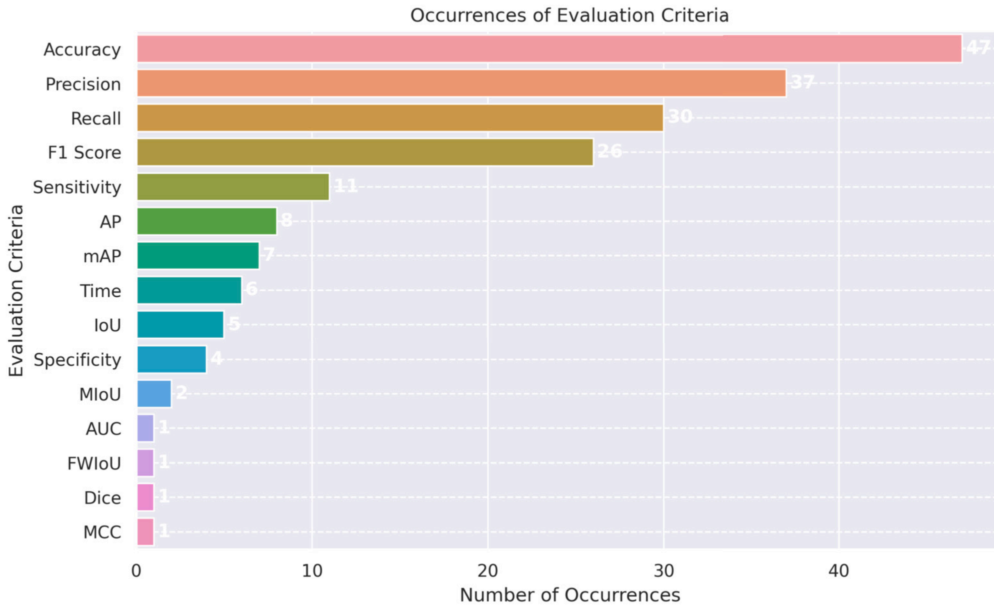

Fig. 10. Exploring evaluation metrics across reviewed papers.

the author's reference, the plant disease detection methodology used, as well as key performance indicators used. These metrics play a vital role in evaluating the effectiveness of disease and pest detection systems in vegetable crops. By examining these results, we can gain insight into which approaches have yielded the best results and emerging trends in this area of research.

Furthermore, we categorize the models based on the widely adopted evaluation metric and accuracy obtained in our study, grouping them into five classes. These classes are defined as follows: Class 1 ranges from 95% to 99.99%, Class 2 from 90% to 94.99%, Class 3 from 80% to 89.99%, Class 4 from 70% to 79.99%, and Class 5 from 50% to 69.99%. Subsequently, we calculate the frequency with which each model falls into these classes. This serves two primary purposes: firstly, to identify the top-performing models among those presented by the authors, and secondly, to assess whether these top models are also the most commonly employed. We assume that a model would be better if it belonged only to class 1 or class 2. Based on our analysis, several models, including DenseNet121, SqueezeNet, InceptionV2, ResNet152, MobileNetV2, ResNet18, VGG16, AlexNet, EfficientPNet, DenseNet169, DCNN, DeepLabV3, EffimobNet, GPDCNN, GoogleNet, VegeCare, and YoloV5, were among the best models according to our criteria (Fig. 11). The significant representation of these models in the highest classes underscores the authors' dedication to enhancing the performance of their proposed models. Furthermore, when examining the most frequently used models, we observe that only VGG16, DCNN, and YoloV5 align with the top-performing models. This leads us to conclude that not all frequently employed models qualify as the best.

4.9. How was the severity of diseases assessed?

Disease severity refers to the extent and impact of a specific disease on plant growth and productivity. Traditionally, this assessment involves visual estimation and is quantified as a percentage or proportion. However, these conventional methods are costly and prone to subjective biases. The integration of deep learning techniques to assess disease severity from images presents significant potential for overcoming these challenges [82,71]. By employing deep learning algorithms, precise evaluations can be achieved, leading to improved predictions of crop yield and the development of efficient management strategies.
Numerous researchers have addressed the challenge of estimating disease severity in vegetable crops. Nevertheless, distinct studies have adopted varied severity definitions to assess disease severity. Out of the 72 studies analyzed, nine utilized image data to estimate the severity of different diseases affecting vegetable crops. Researchers have utilized deep learning algorithms to estimate disease severity in vegetable crops based on well-defined severity levels labeled by plant pathologists. For instance, Mehmet et al. [68] employed the Faster R-CNN model, built on Convolutional Neural Network architecture, to estimate the severity of powdery mildew disease from cucumber leaf images, achieving an impressive 94.86% accuracy. Sharma et al. [81] presented a multiple classification model using a convolutional neural network (CNN) to categorize 1,500 images of mustard crops into healthy and mustard downy mildew (MDM) infected categories, considering four severity levels of the disease. The model demonstrated a high accuracy of 96.66% in multiple classification, indicating its efficiency in accurately distinguishing and categorizing images by severity level. Prabhakar et al. [71] utilized the Foldscope paper microscope to identify tomato leaf blight, followed by assessing disease severity using a ResNet101 deep residual network trained on PlantVillage data covering mild to severe disease stages and healthy leaves. Using pre-trained architectures including Inception-V3, the study achieved an average accuracy of 87.2% in estimating the severity level of Tuta absoluta, considering high, low, and no severity levels of the disease [77]. Verma et al. [93] employed three established CNN models – AlexNet, SqueezeNet, and Inception V3 – to evaluate late blight severity in tomatoes using images from the PlantVillage dataset, categorizing severity stages into early, middle, and late. Utilizing transfer learning and feature extraction with multiclass SVM, AlexNet achieved high accuracies of 89.69% and 93.4%, respectively. Junfeng et al. [29] utilized deep learning algorithms, including AlexNet, SqueezeNet, and Inception V3, to segment late blight disease lesions on potato leaves and assess their severity. The study used images from the PlantVillage dataset, covering three severity stages (early, middle, and late) of the disease. Mandal et al. [59] introduced an automatic deep learning-based method for evaluating the intensity of Phoma blight disease on potato leaflets. Several studies have defined disease severity by quantifying lesion or symptom areas relative to the total leaf area [82]. Kaiyu et al. [51] proposed an accurate method to estimate disease severity from images using an optimized semantic segmentation model with transfer learning and hybrid attention. Validation on late rot and powdery mildew diseases of cucumbers demonstrated precise lesion segmentation and reliable severity estimation (MIoU = 81.23%, FWIoU = 91.89%, $R2$ = 0.9578, RMSE = 1.1385), outperforming other models in complex conditions. Wang et al. [95] proposed a two-step model, DUNet, merging DeepLabV3+ and U-Net for cucumber leaf dis-

Table 4
Deep learning models for disease detection and severity estimation in selected vegetable crop literature.

Model	Sample Size	Species	Severity Estimation	Best model	Performance (in%)					Ref.
					Accuracy	Precision	Recall	F1-score	Others	
VGG19 DenseNet169 Inception-V3 Xception MobileNet DenseNet201 ResNet50	16012 C-GAN synthetic images	tomato	No	DenseNet201	97.11	97	97	97	-	[1]
Hybrid VGG19 MobileNet Inception-V3	Augmented 50000 images	tomato	No	Hybrid	91.2	-	-	-	-	[48]
Hybrid InceptionV3 ResNet152 VGG19	Augmented 3000 images	tomato	No	Hybrid	88.17	82	80	80	-	[78]
Hybrid SVM VGG	-	Potato	No	Hybrid	98	86	89	-	-	[2]
Augmented Resnet50 Resnet152	pepper 8400 images	and tomato	No	Resnet152	99.42	98.57	98.14	98.14	-	[91]
VGG16 VGG19	5100 images	potato	No	VGG16	91	91.31	91.31	-	-	[84]
SqueezeNet AlexNet Inception V3	1909 images	tomato	Yes	AlexNet	93.40	92.99	93.02	93	-	[93]
NasNetMobile MobileNetV2 Xception MobileNetV3	Augmented 109290 images	tomato	Yes	Xception	100	100	100	100	-	[36]
VGG16 InceptionV3 EfficientNetB0	Augmented 3000 images	Chilli	No	InceptionV3	98.83	99.00	99.00	99.00	-	[76]
DCNNs AlexNet GPDCNN	Augmented 35000 images	Cucumber	No	GPDCNN	94.65	-	-	-	-	[102]
DensNet161 DensNet121 VGG6	666 images	tomato	No	DensNet161	95.65	-	-	-	-	[67]
ResNet50 Xception MobileNet ShuffeNet Densenet121 _Xception	Augmented 41263 images	tomato	No	Densenet121 _Xception	97.10	-	-	-	-	[42]
SqueezeNet VGG19 MobileNetV2 NasNetLarge AlexNet DarkNet53 DenseNet201 EfficientNetb0 InceptionV3 ResNet101 ShuffleNet XceptionNet SECNN	Augmented 5100 images	chilli	Yes	SECNN	99.12	-	-	-	-	[62]
					Accuracy	Precision	sensitivity	specificity	Others	
AlexNet MobileNetV2 InceptionResNetV2 Xception ResNet50 VGG16	Augmented 124760 images	Okra Plant	No	InceptionRes NetV2	98.16	97.14	97.2	99.7	-	[44]

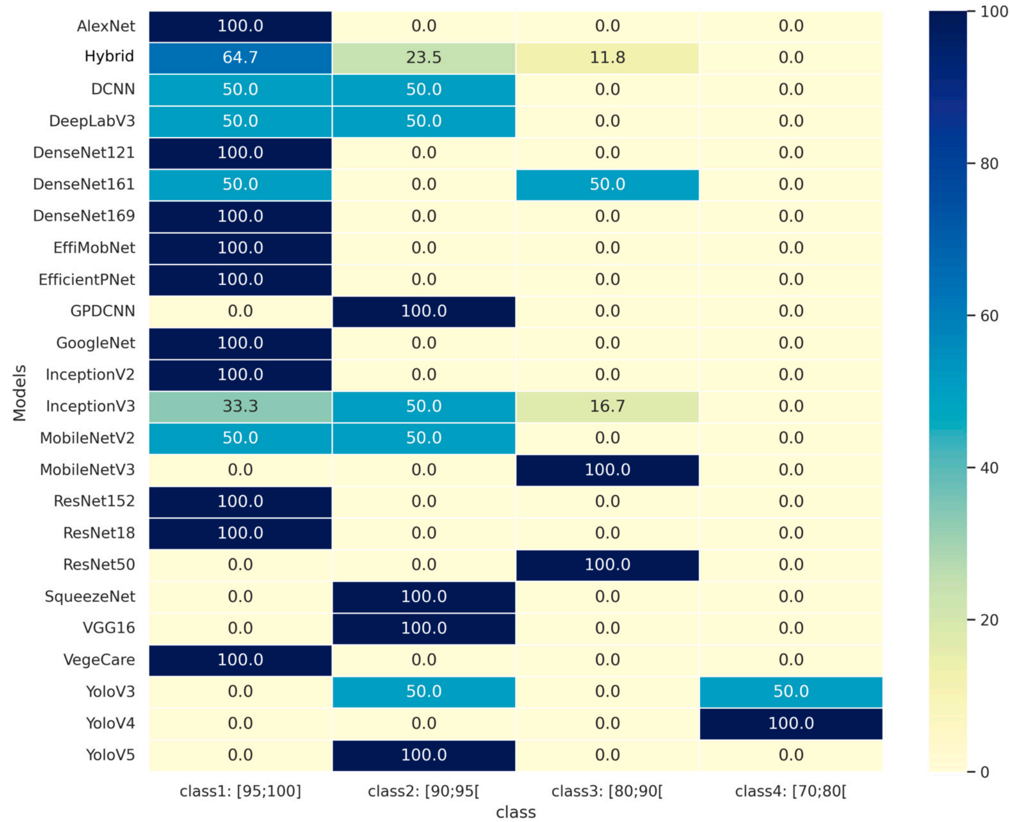

Fig. 11. Model frequency heatmap by accuracy categories.

ease severity classification. DeepLabV3+ initially segments leaves, and U-Net then segments disease spots, enabling accurate severity classification based on the ratio of disease spot pixel area to leaf pixel area. The use of deep learning for disease severity estimation highlights a research gap, as most researchers utilize individual definitions for severity levels, complicating comparisons across different crops and diseases. Furthermore, each plant disease is characterized by unique severity criteria, adding complexity to severity estimation in vegetable crops. Therefore, developing standardized methods is essential. Such an approach would provide a consistent and objective means of estimating disease severity in horticultural crops, facilitating comparisons across crops, regions, and studies [97]. Standardization would also enhance communication and collaboration among researchers, farmers, and policymakers, enabling more informed decision-making for agricultural disease management [97]. The classification and estimation of plant disease severity generally follow the process illustrated in Fig. 12.

4.10. What techniques are effective in improving model performance and mitigating overfitting?

Improving the performance of deep learning models for detecting and classifying plant diseases in vegetable crops is a crucial task in agricultural technology. Overfitting is a common challenge in this context where a model performs well on training data but poorly on unseen data. To address this issue and enhance model performance, several effective techniques have been explored in recent research. For instance, regularization methods like dropout have been widely employed to prevent overfitting. Aldhyani et al. [8] used a dropout rate of 0.5 to prevent overfitting. Data augmentation techniques, such as random rotations and flips, can increase the diversity of the training dataset and reduce overfitting [41]. Out of the 72 studies, 42 used data augmentation techniques such as geometric transformations, color space transformations, and kernel filters. This shows the important role this technique plays in improving the performance of deep learning models. Abbas et al. [1] used C-GAN to generate synthetic images of tomato leaves of various diseases. Furthermore, transfer learning, as demonstrated in studies like [1,3,72,59,51,40,36,4], involves fine-tuning pre-trained models on plant disease datasets, leveraging knowledge from other domains to improve performance. By incorporating these techniques, researchers have significantly developed more robust and accurate deep learning models for vegetable crop disease detection.

4.11. What are the weaknesses of current approaches and authors' perspectives?

Diagnosing and monitoring plant diseases is a complex task requiring accurate disease identification and thorough severity assessment. This study highlights significant progress made by researchers in developing algorithms and models for detecting diseases in market garden crops and estimating their severity. However, limitations and research gaps have hindered the development of comprehensive end-to-end plant disease management systems. In many reviewed studies, researchers train deep learning models under controlled or predefined image acquisition conditions. While achieving precise disease identification in these settings, these models often struggle to generalize effectively across diverse datasets and conditions. Consequently, their performance may not surpass traditional field scouting methods used by farmers. Therefore, establishing robust models capable of accurately identifying diseases globally across varied datasets and conditions is crucial [5]. Abbas et al. [1] and Liu et al. [56] aim to extend disease identification and classification methods to different plant parts like fruits, stems, and branches, exploring various stages of disease development. This holistic approach offers a comprehensive view of how diseases impact plants throughout their growth cycle, facilitating more targeted interventions. Agarwal et al. [4] emphasize the need to expand dataset sizes and diversity by including a greater variety of images and crops. This expansion aims to enhance model capabilities to recognize a wider range of diseases and improve overall detection accuracy. Real-time disease detection and

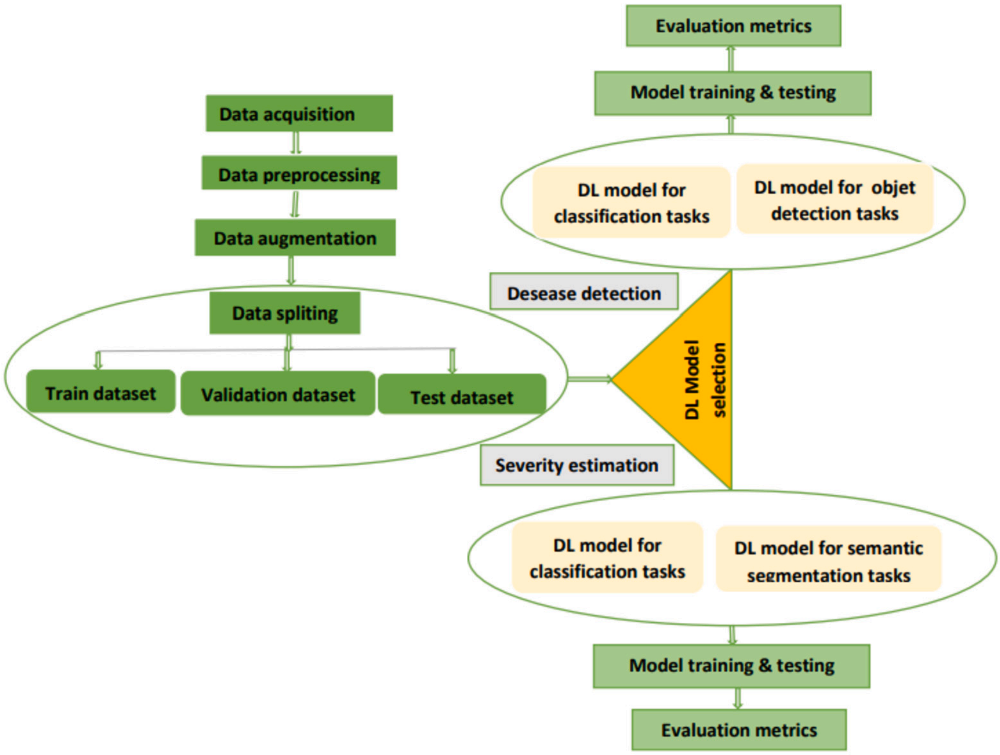

Fig. 12. General flowchart of the deep learning model solutions used.

localization within images remain key objectives. Crispi et al. [20] propose integrating advanced techniques like CNN YOLO for accurate and rapid disease identification, which could significantly benefit agriculture. Moreover, prioritizing the development of user-friendly software and mobile applications in local languages, especially for rural farmers, is essential. This ensures the accessibility of valuable tools to a broader audience, including those with limited technological proficiency [61].

Addressing challenges in crop disease detection involves managing unbalanced classes, enhancing model robustness, and establishing standardized severity definitions. A notable gap exists in methods for estimating crop disease severity in images with multiple leaves.

5. Conclusion

This comprehensive review has provided a detailed analysis of the current state of deep learning methods employed for the detection and severity estimation of stresses and pests affecting market garden crops, such as tomatoes, cucumbers, peppers, and leafy greens. The findings highlight the significant progress made, with convolutional neural networks (CNNs) demonstrating high classification accuracy (F1-scores of 0.85 to 0.92) and object detection techniques like Fast R-CNN and YOLO achieving promising precision and recall values above 0.80. Segmentation approaches, such as Mask R-CNN and DeepLabV3+, have also shown promising results, with IoU scores of 0.75 to 0.85. However, assessing disease severity remains a complex challenge due to the unique criteria for each plant disease and the presence of multiple diseases across diverse crop types, necessitating the establishment of standardized methods. To further enhance the utilization of deep learning, key research priorities include acquiring extensive and diverse datasets, as well as integrating the impact of climate variations on stress manifestation to improve model generalizability and robustness. Looking to the future, integrating deep learning-powered crop disease monitoring with IoT, robotics, and data analytics holds immense potential to revolutionize precision agriculture, leading to improved productivity, sustainability, and profitability in market garden crop cultivation.

CRediT authorship contribution statement

Mireille Gloria Founmilayo Odounfa: Writing – original draft, Software, Resources, Methodology, Formal analysis, Conceptualization. **Charlemagne D.S.J. Gbemavo:** Methodology. **Souand Peace Gloria Tahi:** Methodology, Formal analysis. **Romain L. Glèlè Kakaï:** Validation, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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