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A Systematic Review on Maize Northern Corn Leaf Blight Detection Using AI Models and Aerial Field Images

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Abstract

Northern corn leaf blight (NCLB) or Northern Leaf Blight (NLB) disease remains a global challenge, affecting maize production. Detecting this disease earlier reduces the severity of the disease before it has a devastating impact on crop yield. Recent technological advancements in agriculture have revolutionized crop disease detection and monitoring by leveraging computer vision algorithms for disease detection and UAVs for capturing high-resolution aerial images. However, aerial imagery for NCLB disease is associated with specific challenges, such as occlusion and small object detection problems, which might affect AI model performance accuracy. Therefore, this systematic literature review (SLR) tries to understand the state-of-the-art techniques and methods used to mitigate occlusion and small object detection problems. The study adopts Kitchenham's systematic literature review guidelines to select primary studies for the synthesis analysis. A Boolean search string was utilized on Google Scholar to extract primary studies, and out of 174 studies indexed on Google Scholar, only 7 were selected based on inclusion criteria. The SLR highlighted the AI architectural progression from heavily parameterized CNNs to lightweight models fused with attention modules.

Keywords

Review, Northern Corn Leaf Blight, Drone Imagery, AI Model, Computer Vision

1. Introduction

Northern corn leaf blight (NCLB) disease remains a threat to maize crop yield globally, especially in sub-Saharan African countries such as Zambia. The disease thrives in environments characterized by very humid conditions and warm temperatures, for example during the rainy season in Zambia, which is also the farming season for maize. The disease is caused by a fungus called Exserohilum turcicum, which affects the mesophyll cells of maize leaves. Oliveira *et al.* [1] highlighted the biochemical and physiological changes caused by NCLB that affect maize plants during the growth stages, affecting the photosynthetic process, leading to a necrotic phase and reduced yield productivity.

With the technological advancements in agriculture, drones mounted with cameras and AI models have brought advantages in field monitoring and disease detection compared to manual in-field monitoring and disease scouting tasks. Thus, AI and drones do not just improve throughput but also reduce subjectivity in disease detection. On the other hand, drones mounted with cameras have highlighted the importance of georeferenced image analysis of disease hotspots from drone imagery. By utilizing these state-of-the-art technologies, NCLB-diseased plants are identified through the integration of AI and drone technology. The disease is visually identified by brownish-colored, cigar-shaped lesions on maize leaves that can be captured using RGB cameras mounted on drones and analyzed using deep learning and computer vision algorithms. Drones mounted with cameras have the ability to capture vast amounts of high-resolution aerial imagery of crops in a timely manner, increasing throughput in agricultural monitoring tasks through automated processing of the captured images.

In addition to drones and their applications in crop monitoring, AI models have shown excellent results in crop disease classification and detection, with deep learning algorithms such as convolutional neural networks (CNN) and computer vision-based transformers recording high performance metrics.

This systematic review focuses exclusively on UAV imagery for monotypic disease detection using AI models. To ensure structural rigor, the synthesis specifically covers only primary research utilizing computer vision frameworks and drone imagery that targets NCLB disease as the sole objective function. Primary studies evaluating multi-disease environments or close-up imagery instead of drone data are systematically excluded. By narrowing the scope to monotypic disease, the review isolates the exact technical challenges inherent to NCLB monitoring such as occlusion, and small object detection, thereby ensuring a precise and unconfounded evaluation of the selected computer vision models.

The main objective of this study is to understand the current AI models and architectures for NCLB detection using drone imagery, and to understand the methods and techniques applied in drone imagery to deal with occlusion problems and small object detection. By fulfilling this objective, research gaps can be highlighted or identified, which can be used to propose a roadmap for future experiments for developing agricultural disease detection frameworks using drone imagery, contributing to small object detection tasks and occlusion problems associated with collected agricultural drone data.

2. Related Work

Agriculture has transitioned from traditional farming to Agriculture 5.0 as the most recent advancement in agriculture. This has been made possible through the integration and adoption of various technologies to reduce the strong dependency on human expertise, which is slow and subjective, and to increase throughput. These technologies include technological advances in Agriculture 4.0 (smart farming), robotic devices, big data analytics, and AI. A study overview by Taha *et al.* [2] outlined different technologies for Agriculture 5.0 for precision crop management. The current trend in precision crop management shows a focus on intelligent crop monitoring and solving complex disease and pest detection challenges.

In addition, the integration of UAVs and AI has revolutionized crop monitoring and disease detection tasks, and it has increased throughput by replacing manual field operations, which are slow, time-consuming, and subjective. A review by Zhang Z *et al.* (2023) [3] highlighted the current applications of UAVs in remote sensing for precision agriculture because UAVs provide high-resolution images that enable AI models to accurately extract semantic information for crop monitoring tasks better than satellite images. A survey study by Zualkerman *et al.* [4] highlighted the AI models for crop and weed detection, cropland mapping, and other agricultural tasks. Their findings show that segmentation tasks requiring semantic segmentation need specialized models such as the U-Net model, which uses an encoder-decoder architecture. On the other hand, for classification tasks that do not require excessive feature extraction, standard deep learning detectors such as YOLO, R-CNN, and CNNs are the best fit for this task, while GANs are best suited for data enhancement, augmentation, and data synthesis.

However, AI and UAVs data have some constraints, such as small object detection. A comprehensive survey study on small object detection by Nikouei *et al.* [5] focused on the challenges, techniques, and real-world applications, reviewing articles published in Q1 journals in 2024 and 2025. In their study, the challenges emanate from limited appearance information because of occlusion and background artifacts, scale variation affecting object localization, standard CNN architectures designed for larger objects, and computational complexity. These challenges led to the development of lightweight models, attention modules, image enhancement techniques, multiscale training, and synthetic data generation as new trends for mitigating small object detection.

Similarly, the study by Aldubaikhi A and Patel S [6] highlighted the current limitations of small object detection models, such as the model benchmarks and metrics designed for 32 x 32 pixels (large small objects), which often fail on tiny objects less than 5 x 5 pixels. Therefore, small object detection remains a challenge in computer vision models for tackling real-world complexities.

3. Methods

A systematic literature review goal is concerned with the aggregation of empirical evidence that has been obtained using various techniques and methods. In order to understand the evidence provided and the aggregation process for the objective summaries, a review protocol must be established. A review protocol highlights the plan for how the review is to be conducted following systematic literature review guidelines, ensuring that publication bias is minimized. To meet the study objective to understand the current AI frameworks for NCLB disease using drones and techniques adopted to deal with small object detection and occlusion problems, the study follows Kitchenham's systematic review guidelines for undertaking a systematic literature review. This study follows the iterative eight (8) stage Kitchenham's systematic review guidelines as stated by the authors of [7]-[9]. The following subsections explain Kitchenham's systematic review guidelines and their application in this review.

3.1. Research Questions

When conducting a systematic literature review, having research questions (RQs) helps set the context of the research and guides how data is collected and analyzed to answer the investigation [8] [10]. Thus, a systematic literature review is viewed as a process of aggregating knowledge from empirical studies on a particular topic to address research questions [11]. To objectively achieve the research aim, the research seeks to investigate the following research questions:

RQ1: What AI architectures are used for NCLB disease detection using drone imagery?

RQ2: What data preprocessing methods were used to achieve high performance metrics?

RQ3: What AI model architectural techniques are applied to mitigate occlusion and small object detection problems?

3.2. Search Strategy

A search strategy is essential when conducting a systematic literature review because it ensures that relevant empirical studies of interest are identified. To identify relevant primary sources of primary interest, the study adopts a database search strategy on online research publication databases. The study utilized Google Scholar as the chosen database to perform a Boolean search string because it is a widely used free indexing tool in the field of computer engineering [11] due to its ability to index top journal publication databases such as IEEE Xplore, ScienceDirect, Wiley, MDPI, and other databases like ResearchGate. The Google Scholar search engine maximizes the retrieval density and ensures strict reproducibility since Google Scholar indexes over 90% of elite academic literature, effectively acting as a superset that encompasses records from various databases including top publication databases such as IEEE Xplore, Wiley, MDPI, and ScienceDirect. This study intentionally relies on a singular search engine because automated multi-database queries often introduce irreproducibility due to different Boolean syntax execution and fluctuating institutional subscription walls across indexing services. Furthermore, Google Scholar's natural language processing and citation framework have the ability to index grey literature, preprints and regional institutional repositories, which ensures that highly specific emerging primary studies on UAV imagery based NCLB detection using AI are not missed due to the strict indexing lag typical of traditional databases. Thus, standardizing the search strategy within Google Scholar eliminates inter-database distortions that occur when translating complex Boolean logic.

A Boolean search string ("AI models" OR "AI architectures" OR "Deep learning" OR "CNN" OR "Computer Vision") AND ("Drone-Imagery" OR "UAVs Imagery" OR "Aerial imagery") AND ("Northern Corn leaf blight" OR "Northern Leaf blight") was used to perform a database search to identify relevant primary sources for the study. Additionally, to capture current state-of-the-art AI model architectures and methods, the search results are filtered from the year 2015 to 31 March 2026, the current date the search was conducted. The publication titles retrieved by the search string highlighted the current AI architectures and data preprocessing techniques for UAV imagery spanning a period of 10 years. The search result is processed to select the most relevant publications for the synthesis analysis based on the selection criterion defined in the next subsection.

3.3. Selection Criteria

Selection criteria involve specifying the inclusion and exclusion criteria an article is assessed by to be selected for a systematic literature review study. Having a selection criterion strategy minimizes research bias and ensures the selected articles meet all conditions stated in the inclusion criterion and vice versa. In this study a rigorous two-stage screening procedure was executed independently by the two researchers to reduce selection bias. The researchers evaluated all retrieved titles exported with Zotero reference manager against the predefined inclusion and exclusion criteria during the initial stage of the selection process. Both researchers achieved a high interrater agreement without disagreements. The second stage involved independent examination of the full text of the remaining candidate articles to finalize the inclusion list. Any disagreement and conflicting classification decisions on the full-text examination between the researchers were formally resolved through weekly structured collaborative discussions until a consensus was reached, ensuring the final dataset of the primary selected studies remains entirely objective and free from individual selection bias.

Table 1 illustrates the coded inclusion and exclusion criteria for article selection for the study.

The paper selection process followed the key steps of the PRISMA review process chart adopted by Tedja *et al.* [12]. The key steps can be summarized into four (4) stages, with results feed forward after each stage. These stages are chronologically as follows: database search, articles selected based on title and keywords, articles selected after reading the entire content, and articles used in the research. **Figure 1** selection process diagram illustrates the selection process following

Table 1. Inclusion and exclusion criteria.

Criteria	Code	Description
Inclusion Criteria	IC1	It should be peer-reviewed journals and conference papers, research articles.
	IC2	The title, abstract, or keywords should highlight that drone imagery was used, or the provided full text confirms northern corn leaf detection task using AI models as the primary objective function.
	IC3	The articles should be from the year 2015 to March 31, 2026.
Exclusion Criteria	EC1	Exclude all papers that focused on two (2) or more diseases, including maize diseases.
	EC2	Exclude all review articles, survey articles,
	EC3	Exclude all research that did not utilize drone imagery for northern corn leaf blight detection.

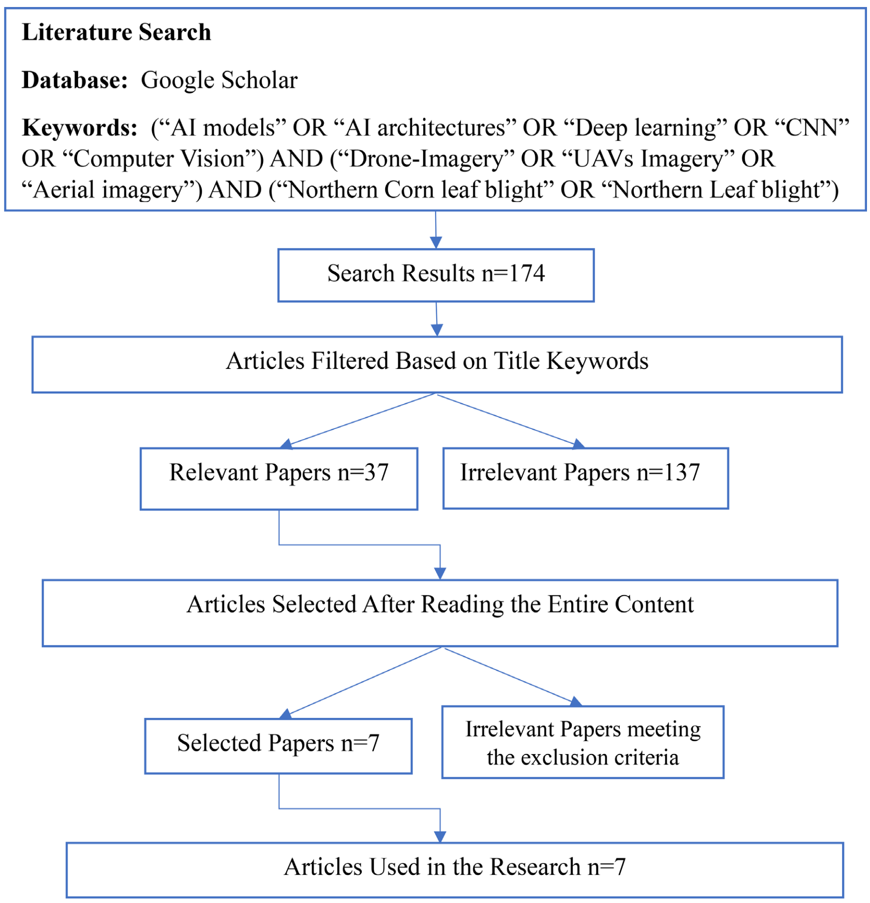

Figure 1. PRISMA election process.

PRISMA election process.

From the database search, 174 articles were found. The filtering process was based on article titles that have maize or northern corn leaf blight or northern blight. A total number of 137 titles did not have one of those keywords; thus, they were irrelevant. After reading the entire content of the 37 relevant articles, only seven (7) papers met the inclusion criteria. Therefore, the research utilizes the seven (7) selected papers for the synthesis review.

Table 2 lists the titles of primary studies based on the inclusion criterion strategy, and a code is assigned to each paper title.

Table 2. Selected papers.

Code		Paper Title(s)	Year	Publisher
1	P1	Automated Detection of Corn Leaf Blights in Natural Light Images Captured by Drones Using Deep Learning Frameworks [13]	2024	IEEE
2	P2	Quantitative phenotyping of northern leaf blight in UAV images using deep learning [14]	2019	MDPI
3	P3	A weakly supervised approach for disease segmentation of maize northern leaf blight from UAV images [15]	2023	MDPI
4	P4	Autonomous Detection of Northern Leaf Blight directly from aerial imagery [16]	2019	WILEY
5	P5	A method for segmenting disease lesions of maize leaves in real time using attention YOLACT++ [17].	2021	MDPI
6	P6	Maize plant disease prediction from UAV images for precision agriculture using fusion of multimodal [18]	2023	IEEE
7	P7	Accurate recognition and segmentation of northern corn leaf blight in drone RGB images: a CycleGAN-augmented YOLOv5-Mobile-Seg lightweight network approach [19]	2025	Science Direct

3.4. Quality Assessment Criteria

Establishing a quality assessment strategy is important when conducting a systematic literature review, as it ensures bias is minimized and the study is conducted objectively. A quality assessment strategy is a checklist with specific guidelines for selecting the primary sources of empirical studies to be reviewed in a systematic review, apart from the inclusion and exclusion criteria. In this study, a checklist containing seven (7) generic questions was utilized to assess the quality of an article by assigning scores to each article using a three-point Likert scale. The researchers ensured that the assessment questions are balanced in accordance with the research questions.

The first question assesses whether the study targets NCLB and uses drone imagery for the research experiment (Q1). This question sets the theme of the disease under investigation. After establishing the target of the study, the second question (Q2) focuses on the AI methodology used in the paper to ensure the paper describes the model architecture and the learning task it is trying to solve. (Q3) checks whether the study compares various models or AI model baselines to justify the performance improvements. Drone imagery datasets for maize NCLB disease are limited publicly online, and to ensure study variability based on studies, (Q4) ensures the study reports the dataset source, labelling, and description. Furthermore, (Q5) checks the image preprocessing and augmentation techniques used in the paper, such as image resizing, image tiling, and any domain adaptation methods described. (Q6) assesses evaluation rigor; the paper should report relevant performance metrics applicable to the choice of AI architectures used in the paper. A report on performance metrics also provides empirical evidence for the methods applied during the experimentation and ensures research reproducibility. Lastly, (Q7) checks for evidence of work that addresses real-world challenges such as small object detection, occlusion, and environment variation. Table 3 highlights the quality assessment questions used to evaluate each primary study and supports the study objective of identifying the AI model frameworks or architectures for NCLB disease detection using UAV imagery, with specific methods that address occlusion problems and small object detection.

Table 3. Quality assessment questions.

Code	Question(s)
Q1	Does the study investigate NCLB detection from Drone-Imagery?
Q2	Does the study utilize any computer vision AI framework for NCLB disease detection?
Q3	Does the paper state the dataset source, description, and annotation?
Q4	Are experiment results for AI models reported?
Q5	Does the research utilize more computer vision models or architectures for performance comparison?
Q6	Are there reported data preprocessing and augmentation methods applied for the experiment?
Q7	Are there specific methods applied to reduce occlusion problems and to improve small object detection?

3.5. Quality Assessment Score Evaluation

After selecting papers, quality scores are computed based on the relevance, rigor, reporting, and credibility criteria. This structured scoring approach reduces subjectivity during the evaluation assessment of each included study, and the total quality score for a paper is obtained by summing all the scores across all criteria. To obtain the scores for paper quality assessment, a three-point scale is used, where yes is given a score of 1 when a paper clearly satisfies the criteria, 0 is assigned to no when the criteria are not reported clearly, and lastly, somewhat is assigned a value of 0.5. Papers with a higher quality assessment score are classified as high quality because they provide clear methodology, strong evaluation evidence, and strong alignment with the review's objective and focus area. On the other hand, studies with a low-quality score are classified as low quality due to weak reporting, limited relevance to NCLB detection using drone imagery, and less emphasis on occlusion and small object detection problems. Therefore, more robust interpretation of results and conclusions can be drawn from studies with higher scores, exposing suitable AI architectures and processing techniques for drone imagery data for NCLB disease detection using computer vision algorithms.

The study adopts an 8-point maximum possible score to evaluate the methodological integrity of the selected studies by applying a structured quality assessment (QA) framework. The study established a categorization threshold to classify studies into high, medium and low-quality cohorts based on the paper's cumulative total QA score obtained. To interpret these scores objectively, studies achieving a cumulative score of 7.0 to 8.0 are classified as high quality, demonstrating robust data curation process, rigorous validation and reporting of results and transparent model architecture for drone-imagery-based NCLB disease detection. Papers between 5.0 and 6.5 points are designated as medium quality, indicating valid scientific contributions that possess minor limitations in methodology when dealing with small-object detection. Any study scoring below 5.0 points is categorized as low quality, signifying critical methodological deficiencies or insufficient documentation that answer the study questions. To ensure the review's conclusions rest on reliable evidence, only studies categorized as medium or high quality are considered to influence the final synthesis.

Table 4. Quality assessment scores.

Quality Assessment Scores		P1	P2	P3	P4	P5	P6	P7
Relevance	**Q1**	1	1	1	1	1	1	1
	Q2	1	1	1	1	1	1	1
Results Reporting	**Q3**	1	1	1	1	1	1	1
	Q4	1	1	1	1	1	1	1
	Q5	1	0	0	0	1	1	1
Rigor	**Q6**	1	1	0.5	1	1	1	1
	Q7	1	0	0	0	1	0	1
Credibility	Σ(Q3, Q6, Q7)	0.5	0.5	0.5	0.5	1	1	1
Total		**7.5**	**5.5**	**5**	**5.5**	**8**	**7**	**8**

The quality assessment questions were grouped to assess paper relevance, results reporting, rigor, and credibility. Table 4 illustrates the quality assessment scores for each primary paper. Relevance determines if the research solves the problem of NCLB disease detection using AI models and drone imagery. Results reporting determines whether the results of the experiments were reported in the paper. Research rigor determines the scientific backbone that ensures the methodology is sound, and lastly, credibility ensures research trustworthiness and reproducibility.

3.6. Data Extraction Method

The research utilized the Zotero reference manager to extract article data from the database search results. The data extracted by the Zotero reference manager include authors' names, titles, years, abstracts, publisher, type of paper [20], etc. The data obtained by Zotero was exported to a .csv file to create a Data Frame for further manipulation using the Python programming language and the Pandas library to filter paper titles using the keywords northern corn leaf blight or northern leaf blight. A minimized dataset containing 37 records was created from the filtering results and manually analyzed strictly following the inclusion and exclusion criteria as described in subsection 3.3 Selection criteria.

3.7. Data Synthesis Method

The research adopts a narrative synthesis method, which emphasizes understanding the study context and methodologies of included studies without statistical pooling [20]. Therefore, the research data synthesis method focuses on descriptive aggregation of research findings, focusing on findings across studies, focusing on themes, similarities, and patterns, and incorporating subjective interpretation [20].

To ensure a transparent analytic trace from the primary literature to the final review conclusion, the study adopts a standardized data extraction matrix with six (6) explicit descriptive and technical fields highlighting the paper's core technical methodological themes. These fields were coded systematically from each of the seven selected primary studies and mapped directly onto the review's research questions RQ1, RQ2, and RQ3 to generate synthesis themes. The fields are model/architecture, model attention mechanism, core technical focus, dataset characteristic, data preprocessing/augmentation, and occlusion/small-object solution. The core themes are as follows:

Theme 1: Computer Vision Architecture and Core Technical Focus—the theme maps to RQ1. The information extracted specifies the performance metrics, core deep learning network and backbone adopted and the application scope of the computer vision model.

Theme 2: Dataset Characteristics and Curation—this theme is mapped to RQ2. To evaluate data architectural constraints, the data extracted include data augmentation and preprocessing methods, and dataset source.

Theme 3: Structural Adaptations—this theme is mapped to RQ3, it addresses the techniques and mechanics deployed in the structural design of deep learning network to mitigate occlusion and small-object detection problems which are associated with UAV data. The extracted and recorded data focused on detailing model attention mechanism.

The qualitative findings from the source papers were seamlessly translated into direct empirical answers for the study's research questions by clustering these six (6) standardized data fields into localized synthesis themes.

4. Results

The synthesized results for this SLR utilized seven (7) papers with high-impact technical narratives focused on AI evolution, architectural diversification and optimization, and data optimization for NCLB disease detection from drone imagery acquired from the year 2019 to 2025. The results highlight a shift from traditional CNN architectures to real-time segmentation and lightweight, high-precision architectures such as YOLOv5-Mobile-Seg. The AI architecture progression chart in Figure 2 (AI architecture progression), highlights the progression of different AI architectures in detecting NCLB applications using aerial images.

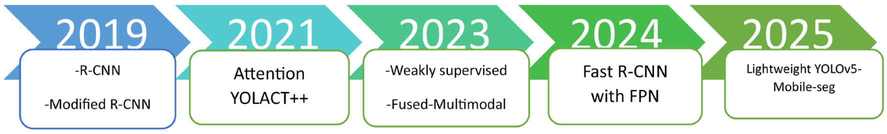

Figure 2. AI Architecture Progression.

Furthermore, the studies highlight the importance of data curation and optimization to increase AI model performance, efficiency, and accuracy; for example, the CycleGAN in paper **P7**. A results comparative Table 5 demonstrates the challenge-solution mapping of the selected papers in the SLR to answer the research questions.

Table 5. Paper comparison.

Paper Code	Model/Architecture	Core Technical Focus	Data Optimization	Occlusion/Small Object Solution
P1	Deep Learning Framework	Natural Light UAV Imagery	Preprocessing for lighting	Feature Pyramid Network (FPN)
P2	Modified R-CNN with a ResNet-101 backbone	Quantitative phenotyping—(NLB lesion segmentation)	High Resolution Imagery cropping area of interest -Standardized image size -Labeling	-
P3	Weakly Supervised Segmentation	Lesion Segmentation and Pseudo-label extraction	Label-efficient learning -Image slicing, then resizing	Pixel-level attention (ACoL)
P4	CNN (ResNet-34)	Aerial Detection	Direct Inference	Spatial Pooling and Scale-Invariant Layers
P5	Attention YOLACT++	Real-time Segmentation	High Resolution Imagery cropping area of interest -Standardized image size -Labeling	Spatial Attention Modules
P6	Multimodal Fusion (Xceptional + DenseNet-121)	Prediction-Classification	Background removal using OTSU and K-Means clustering -Image resizing -Gaussian blur, etc.	-
P7	YOLOv5-Mobile-Seg (YOLOv5 with Mobilev2 backbone + Mobile-Net bottleneck)	Lightweight Segmentation model For real-time monitoring	CycleGAN Augmentation	Lightweight Conv Layers Spatial Attention Modules

4.1. RQ1: What AI Architectures Are Used for NCLB Disease Detection Using Drone Imagery?

The synthesis of the selected studies has shown the technological landscape evolution of deep learning algorithms for NCLB disease detection from Convolutional Neural Networks (CNN) utilized in papers (P2 and P4) to real-time detection models that focus on fine-grained pixel-level analysis like the Attention YOLACT++ in paper (P5). In addition, the synthesis of selected studies highlighted that early works utilized standard backbones to identify NCLB disease lesions. For example, paper (P2) utilized a Res-Net-101 as the backbone for the R-CNN model, and paper (P4) utilized ResNet-34 as the backbone for the CNN architecture. The CNN backbone consists of spatial pooling and scale-invariant layers that perform specific roles for feature extraction by aggregating shallow features and rich semantic information [21] into a feature map before forwarding it to the neck and head of a CNN. Based on the findings, ResNet architectures are the most widely used as backbones for CNN architectures because they can achieve high accuracy and have high performance in object detection [22].

Furthermore, there is a noticeable transition from traditional feature-based models to Hybrid and Lightweight models in paper (P7), and the Multimodal Fusion model in paper (P6). Earlier papers (P2, P4) established the efficiency of deep residual networks for NCLB disease phenotyping, increasing throughput in disease detection as compared to manual assessments, which are slow and subjective. Recent studies by authors of (P5 and P7) emphasized architectures for real-time segmentation of NCLB disease lesions. However, deep learning models for the semantic segmentation task are mostly considered for real-time phenotyping tasks because the architectures focus more on high-performance accuracy [23], but less attention is given to computational cost and inference speed for resource-constrained processing on embedded platforms [24]. To address these challenges, paper (P7) proposes a lightweight segmentation model, the YOLOv5-Mobile-seg architecture, to attain low computational complexity suitable for edge-node processing of drone imagery for NCLB disease with high accuracy.

With the current developments of lightweight models as a way of enhancing the performance of semantic segmentation architectures, the integration of spatial attention modules in paper (P7) marks a transition from general feature extraction to selective focusing, which is essential for isolating different sizes of NCLB lesions from sophisticated backgrounds. In addition, model pruning and ablation may increase model performance, as evidenced by the average precision (AP) increments in the experimental results of (P7).

4.2. RQ2: What Data Preprocessing Methods Are Used in Order to Achieve High Performance Metrics?

Drone imagery data is affected by environmental noise, such as when the NCLB lesion color is similar to other objects such as maize tassels, soil, and other crop blights, which remains a bottleneck in UAV-based NCLB detection. Therefore, it is essential to ensure high data quality and to utilize data optimization strategies when working with such a complex dataset that is greatly affected by environmental noise. From the synthesis of selected studies, three (3) dominant data optimization strategies were identified, addressing the credibility gap to ensure the dataset is reliable for AI model training. These strategies are identified as synthetic data generation, weakly supervised learning, and data augmentation.

4.2.1. Data Augmentation

Data augmentation strategies consist of applying various types of transformations to the training dataset for the purpose of artificially increasing data diversity [25]. The most widely used transformations include rotation, flipping, zooming, scaling, and brightness adjustment. Almost all the papers in this research adopted these transforms. In a similar approach, all the papers have performed image cropping or resizing before applying other data augmentation transformations for the sake of reducing computational cost during the training process if the original drone image size was used. The drone-captured images are very high in resolution, which requires data compression techniques such as applying slicers, grids, and cropping to mitigate challenges in data management.

4.2.2. Weakly Supervised Learning

The authors of (P3) introduced a weakly supervised segmentation model for NCLB segmentation by generating pseudo labels of NCLB lesions for training the model. Their proposed model achieved 84.6% precision, proving that high performance can be achieved without exhaustive manual annotation. Weakly supervised learning is a paradigm in the machine learning taxonomy, which sits between supervised learning and unsupervised learning [26], and machine learning models are trained using a small amount of labeled data and a large amount of unannotated data. There are three approaches under weakly supervised learning, which are incomplete supervision, inexact supervision, and inaccurate supervision [27] [27].

4.2.3. Synthetic Data Generation

The paper (P7) adopted a deep learning-based data augmentation by utilizing CycleGAN to perform data optimization, to artificially increase the dataset images, NCLB lesion size variability, and variant lighting and illumination conditions depicting real-world scenarios. This approach of utilizing GANs for data optimization reduces labelling workload, and also the deep learning-based augmented dataset improves model performance and robustness under complex situations where occlusion problems are often encountered [28].

4.3. RQ3: What AI Model Architectural Techniques Are Applied to Mitigate Occlusion and Small Object Detection Problems?

The main objective of this SLR is to investigate the methods and techniques applied to handle drone imagery problems focusing on NCLB disease detection, focusing on small object detection and occlusion problems.

4.3.1. Small Object Detection

Recent studies (P3, P5, P7) have shown that implementing Attention modules has become the standard for the segmentation task and for achieving high performance, although the papers did not explicitly mention small object detection. Paper (P3) adopted the ACoL pixel attention model for feature extraction in a weakly supervised learning setting. The module utilizes two (2) parallel classifiers, namely classifier A path, which uses an Adversarial Mechanism to learn to detect the most prominent part of the object, then erases it from the feature map before passing it to the other classifier. Meanwhile, the classifier B path is trained to perform the complementary learning of the remaining regions of the object that the first classifier did not focus on, then fuses the feature maps together [29]. In addition, paper (P5) introduced the Convolutional Block Attention Module (CBAM) to improve the accuracy of the YOLACT++ model architecture, and the performance metrics results were tremendously good, ranging above 98%. In the same context, the paper (P7) introduced the CBAM integrated with the Fused MobileNet Bottleneck Convolution Module (FusedMBConv), and the model achieved an average precision of 88.0% on the segmentation task and 88.8% on the recognition task. Therefore, this mechanism can successfully increase performance.

The CBAM comprises channel attention mechanism (CAM) and spatial attention mechanism (SAM) modules that enhance the focus on crucial locations of features while suppressing the irrelevant ones [30], and the advantage of these modules is that they improve the classification performance of CNNs [31] without adding a lot of network parameters [32] since the CBAM is a lightweight module [33]. Furthermore, the Fused-MBConv module improves the recognition accuracy of occluded objects [34] and improves computational complexity.

Therefore, these attention models are essential when mitigating challenges associated with small object detection, such as background noise, as these modules can learn to isolate high semantic information from noise.

4.3.2. Occlusion Constraints

The occlusion problem remains a challenge in computer vision, especially when detecting objects from drone imagery. This might lead to reduced AI model accuracy and high complexities, such as intricate development processes involved in developing, training, and deploying AI systems to mitigate the occlusion problem. According to Huang Y *et al.* [35], the use of data augmentation, attention modules, and improved loss functions can solve occlusion problems. Since all the selected papers for this synthesis have utilized either data augmentation techniques or attention modules, this may solve the problem of extracting sufficient features due to occlusion.

5. Discussion

The adoption of lightweight models such as YOLOv5-MobilevNet-seg ensures the sustainability of AI models, especially on edge devices, which are resource-constrained devices for real-time inference [36]. The development of lightweight AI models is the new trend and is vital in achieving low energy consumption and low computational cost, as well as achieving higher accuracy. For example, the model by Musa A *et al*. [37] proposed a model that is three times smaller than the vanilla CNN and achieved 97% accuracy. Therefore, by utilizing these lightweight models and optimization techniques, such as data augmentation and model pruning, the model training converges faster, and inference is faster, especially on complex datasets [38]. On the other hand, standard deep learning models, due to their huge number of parameters and high computational cost, have limited application, especially on resource-constrained embedded systems, even though they can achieve high performance accuracies.

The recent advancements in lightweight AI models have facilitated the development of attention modules such as the CBAM, which assist the model's ability to focus on spatial features, extract semantic information, and enhance the training performance of AI models. The CBAM utilizes both the CAM and SAM to extract more efficient features for feedforward CNN architectures, especially for the NCLB disease segmentation task from aerial images. Drone imagery datasets for NCLB disease are inherently complex, characterized by numerous non-target objects and elements such as tassels, maize silks, soil, occlusion, weeds, and NCLB lesions of varied morphology and length, which might hinder smooth model training. By leveraging CBAM, the model can suppress background noise, since the CAM focuses on channel importance and applies attention weights based on the aggregation of channel information obtained from Global Average Pooling and Global Max Pooling, while the SAM focuses on spatial importance by compressing channels through average pooling and max pooling. Thus, employing attention modules such as CBAM enables the CNN model to concentrate on important features when handling such complex datasets, ensuring robust learning and improved performance.

Traditional CNNs such as R-CNN have produced good results, but their application remains limited because of their limitations on generalizability; they require high-resolution images in order to perform pixel-level localization of objects. Also, they suffer from vanishing gradient problems, which can affect the model's accuracy. Subsequently, the adoption of weakly supervised learning reduces annotation workload but, on the other hand, increases computational cost because another independent CNN is utilized to generate pixel-labels. On the same note, weakly supervised learning utilizes the ACoL module for object localization by leveraging its two parallel classifiers that identify discriminative and complementary object-related regions through adversarial erasing operations [29]. Also, for the classification of NCLB diseased and healthy crops, a multimodal fusion proposed by Mishra *et al*. [18] produced a 96.95% accuracy on the validation set using UAV imagery.

The study has exposed the scarcity of heterogeneous drone imagery datasets of NCLB disease. Most research studies utilize the OSF NCLB dataset by Wiesner-Hanks *et al*. [39]. This lack of homogeneity in the use of one dataset produces AI models that lack environmental variability, which might affect the model's robustness on pictures taken from other maize fields with different soil colours. Thus, models trained on a singular dataset may fail when deployed in other regions with different soil colours and types; for example, in Zambia, there is red, black soil, etc. Therefore, it is important to utilize synthetically generated data to represent various conditions, and also as a solution to the data bottleneck in agricultural AI, where specialists are required to label vast aerial image datasets, poor dataset quality, difficulty in data acquisition, and limited data required for robust model training [40].

6. Conclusions

This SLR evaluated the technical evolution of NCLB disease detection using drone-acquired images across seven (7) primary studies spanning from 2019 to 2025, by synthesizing three thematic areas: the technical evolution of AI architectures, data quality and optimization strategies, and solutions to mitigate occlusion and small object constraints. The key observations are as follows:

1) The research has transitioned from standard CNNs utilized in papers (P2) and (P4) to lightweight and attention-based models such as YOLACT++. This demonstrates that the research field is now shifting towards a balance between computational efficiency and high-performance accuracy suitable for embedded devices for real-time monitoring and inference.

2) Also, the synthesis highlighted two unique data optimization and curation approaches to overcome noisy field data and quicken the data labeling and curation tasks. The adoption of CycleGANs for synthetic data generation not only increased the dataset size but also increased data variability of NCLB lesions and environments based on fewer samples rather than performing the job of capturing and manual labeling. In a similar fashion, weakly supervised utilized in paper (P3) produced strong results.

3) Recent studies have demonstrated that the utilization of attention modules such as the CBAM improves the small object detection problem, and they improve performance due to their architectural mechanism. Also, model ensembling ensures robustness and increased performance.

4) While CycleGANs address data scarcity and variability, future frameworks should focus on federated learning or multi-environment learning. This allows Zambian researchers and developers to collaborate and develop robust AI disease detection systems targeted specifically for Zambian farmers.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Abbreviation

NCLB	Northern Corn Leaf Blight
NLB	Northern Leaf Blight
AI	Artificial Intelligence
CNN	Convolutional Neural Network
CBAM	Convolutional Block Attention Module
CAM	Channel Attention Module
SAM	Spatial Attention Module
SRL	Systematic Literature Review
UAV	Unmanned Aerial Vehicle(s)
ACoL	Adversarial Complementary Learning
GAN	Generative Adversarial Networks
RGB	Red Green Blue (camera colour channels)
R-CNN	Region-based Convolutional Neural Network
AP	Average Precision
YOLO	You Only Look Once
Fused-MBCov	Fused MobileNet Bottleneck Convolution