IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 13, No. 3, September 2024, pp. 2459~2471
ISSN: 2252-8938, DOI: 10.11591/ijai.v13.i3.pp2459-2471

Review of image processing and artificial intelligence methodologies for apple leaf disease diagnosis

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Article Info

Article history:

Received Aug 17, 2023
Revised Jan 25, 2024
Accepted Mar 5, 2024

Keywords:

Apple leaf disease
Artificial intelligence
Detection
Image processing
Symptoms

ABSTRACT

Apple leaf disease (ALD) potentially affects the apple tree's health by reducing fruit yield and its capability to grow healthy. The prime purpose of the proposed study is to review and assess the strengths and weaknesses associated with the frequently exercised methods of ALD diagnosis using image processing and artificial intelligence (AI). Although these are widely adopted in recent studies, the core notion is to find the pros and cons associated with the practical viability. A desk research methodology is undertaken to carry out proposed review work where a database of recent scientific manuscripts is collected and studied very closely. The existing approaches are reviewed concerning identified problems, adopted solutions, advantages, and limitations. Finally, the paper contributes towards offering insight into potential research gap which will guide the upcoming researchers to make wise decisions for planning their models. The results acquired from this review work show that generalized challenges of ALD are not addressed, less emphasis on illumination variability, reduced target to minimize complexity, lesser evidence towards real-time processing, no evidence towards interpretability, limitation of available dataset, and tradeoff-between image processing and AI.

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1. INTRODUCTION

The health of any plant can be primarily diagnosed from the visuality of its leaf [1]. Various forms of adverse infection are notably witnessed over a period where the natural form of the leaf distorts and showcases an abnormal morphology [2]. This paper discusses apple leaf disease (ALD), which could originate from viral, bacterial, and fungal infections [3]. The presence of ALD potentially affects yield losses, minimizes apple quality, and reduces the effectivity of the photosynthesis process. In apple, the viral diseases are conventionally known as mosaic virus, chlorotic leaf spot, and stem pitting virus [4]. All these forms of viral infection result in grooves of pitted depression on the leaf's surface area or cause yellow spots affecting photosynthesis and reducing the vigour of leaves—the bacterial infection in apples results in bacterial spots and fire blight. Sometimes, small dark spot-on apple leaves with yellow halos cause burned leaves, blackening, and wilting [5]. The fungal infections are frequently noticed in leaves of apple tree causing wide ranges of abnormalities e.g. scab, mildew, and rust [6]. Usually, fungal infection results in pustules on leaves, lesions with orange-brown galls on leaves, or generates powdery coating affecting photosynthesis, causing scaly lesions. Irrespective of any form of ALDs, the complete structure of the tree, including blossoms and fruit, gets adversely effected. Presently, there are various means to diagnose ALD, where the most common and faster one is by visual inspection. All the primary and common symptoms associated with ALD, e.g. wilting, discoloration, lesions, and spots, can be easily accessed and evaluated by visual inspection. However, visual inspection encounters a more significant challenge if the area of an apple orchid is vast. This challenge can be mitigated by adopting various available mechanisms of capturing the images via drone-based cameras and visual sensors in agriculture [7], [8]. Other approaches can be used to acquire apple leaf images, e.g. field surveys, image-sharing platforms, and existing datasets. However, the problems start after acquiring an image gathered by various means. The acquired images have various problems during the acquisition step itself. The lowlight, fluctuating illumination, anomaly in leaf orientation, overlapping, and occlusion, pose significant challenges in ALD diagnosis. Image processing and artificial intelligence (AI) have jointly been used to improve the accuracy of existing implementation. Hence, it demands an elaborate yet crisp discussion of the effectiveness of existing methods towards ALD diagnosis. It is noted that the detection of ALD is usually carried out by image processing or AI-based schemes, whose details are provided in section 3 onwards. The pros of these existing schemes are that they offer a comprehensive predictive procedure that can foretell the presence of ALD with higher accuracies. The cons of these existing schemes are that they are computationally extensive and don't cater to the demands when deployed on practical grounds. However, there is no denying that AI and image processing-based mechanisms are always the better alternatives towards ALD detection. This is the prime motivation to investigate the strengths and weaknesses of these existing solutions so that better forms of computationally viable and cost-effective solutions can be evolved. The prime motivation is also to ensure the newly evolving methodology for detecting ALD should work in real-time, as seen in the work of Yağ and Altan [9]. The prime aim of this paper is to present a discussion of the most notable and recent contributions towards ALD diagnosis.

This review work is the first of its type from an ALD perspective, as there is no reported review work towards ALD detailed in such elaborated insights. The contribution of this article are as follows: i) introduces a straightforward methodology to carry out proposed review work that is not only simple but also results in distinct and highly relevant research work on ALD, ii) introduces recent techniques using image processing and AI towards ALD diagnosis and evaluates its strength and weakness, iii) highlights current research trend to showcase a distinct observation about frequently adopted techniques as well as ignored approaches with missing gaps, and iv) crisply highlights prominent research gap associated with existing methodologies that are required to be addressed. Unlike any existing scheme, the proposed paper offers a more precise insight towards the strengths and weaknesses associated with currently deployed problem solutions in ALD detection, which will give better decision-making for future researchers.

The novelty of the papers are i) the paper presents crisp information about all the potential diseases of leaves being researched in existing times, ii) the manuscript identified frequently adopted methodologies to be image processing and AI, and their strength and weakness has been highlighted, iii) a significant and compact representation of research trend is presented which offers more insight towards the frequently adopted technologies in more elaborated manner, and iv) the paper offers highlights of essential research gap which has found not to be addressed in existing problem solution. The paper is arranged as follows: discussion towards compact insight of ALD is carried out in section 2, the adopted methodology is briefed in section 3, section 4 illustrates about existing studies on image processing-based ALD, section 5 discusses AI-based methodology for ALD detection, section 6 discusses dataset, while research trend is discussed in section 7. The pin-pointed highlight of the research gap is presented in section 8, while section 9 concludes the paper.

2. INSIGHTS ON APPLE LEAF DISEASE

Leaf is the primary indication of the health status of an apple plant, and using various image-capturing media, it is now not so challenging to capture leaf images. Hence, investigation of ALD results in proper feedback towards tree health, fruit quality, yield reduction, disease spread, management cost, and environmental impact [10], [11]. The disease can be identified by various means from the leaf images. The presence of circular spots and the twisted shape of the leaf are some primary indicators. Scabs and lesions of various forms are the following forms of indicators of ALD. Some of the standard indicators of ALD being investigated are as follows:

– Blotch: leaf blotch or premature leaf fall is usually confirmed by circular patches with a dark green on the upper leaf surface, leading to 5-10 mm of brown spots that darken over time (Figure 1(a)). The disease also spreads to the lower leaf surface slowly. Acervuli of a small black type are formed on the leaf surface. This disease usually occurs in heavy rainfall during fruit development [12].
– Mosaic: this ALD is formed when a mosaic virus attacks the apple tree, leading to the generation of bright to pale spots of cream color on spring leaves (Figure 1(b)). When subjected to heat and sun exposure, they turn necrotic. Such viruses also result in line patterns, chlorotic rings, distortion of leaves, and spots

on chlorotic leaves, potentially affecting apple leaf's stunting and sizes. This virus infects the apple tree and spreads its infection to neighboring plants and trees [13].

- Spot: the presence of spots or blights on the apple leaf generally occurs in early summer or late spring, resulting in small brown round spots of quarter inches (Figure 1(c)). These spots are also identified by their purple border. It turns to ash grey with passing time, resulting in enlarged spots. It also results in defoliation, mainly seen with heavily infected apple leaves. This disease is mainly observed in plants cultivated in elongated wet conditions and spreads quickly to neighboring branches and trees [14].
- Rot: there are various types of rot found in the apple leaf. Black rot canker symptoms surface during early spring in purple and specks on the upper leaf surface (Figure 1(d)). Such disease spreads more in the winter season in moist conditions mainly. Other types of rot are usually seen on collars or fruit [15].
- Cedar apple rust: this is mainly formed due to fungal infection on the apple leaf and is characterized by red to orange spots on the leaf surface (Figure 1(e)). The leaf is damaged, and so is the fruit of this disease. Different shapes are formed on a leaf, but the most noticeable one is on red cedar. The infections grow more in the prolonged rainy season, resulting in spores and lesions on the leaf surface [16].

(a) (b) (c) (d) (e)

Figure 1. Classes of ALD (a) blotching, (b) mosaic, (c) spots, (d) black rot, and (e) cedar apple rust

However, there are some sustainable solutions to deal with all the diseases, conditions seen on apple leaves. However, the most challenging one is to identify the disease in the form of an image. At present, detection of ALD is carried out by laboratory tests, comparison with reference manual, symptom analysis, and visual inspection. The current papers discuss visual inspection, where images are captured by trained individuals and significant attributes of diseases are examined based on leaf arrangement, texture, size, shape, and color. The following section discusses the methodology used for carrying out this review work.

3. ADOPTED METHODOLOGY

A systematic literature review has been conducted to investigate the strengths and weaknesses of existing methodology towards ALD. There is no significant publication of a review paper discussing methods used for ALD detection while existing studies are mainly related to the discussion of implementation schemes. Therefore, a specific methodology is adopted in the proposed review work to accomplish the goal of review work in a simplified way. Figure 2 highlights the adopted methodology inclusive of a specific set of sequential operational blocks as described:

- Data identification: this is the first stage of the proposed review work, which pertains to identifying the context of the study, i.e. identifying all scientific articles with a discussion of ALD published between 2018-2023. In this case, the database consists of all research articles, including open-access articles, magazines, books, conference papers, journals, symposium articles, and genuine blogs that are collected and bookmarked. A total of 8,431 articles have been collected which deals with exclusively ALD only.
- Prelim screening of articles: all the 8,431 articles have been screened precisely concerning title and contents within an abstract to ensure that correct articles towards ALD have been acquired. While screening the abstract, it is noted that the name of the implemented methodology is clearly mentioned, and so is the result. It assists in making initial decisions towards filtering the collected articles based on relevance.
- Primary filtering: this process consists of two steps to confirm that filtering is carried out to consider the studies related to ALD only with an elaborative discussion of the implementation strategy. The inclusion and exclusion criteria govern the first step towards primary filtering, while the second stage towards primary filtering is ascertaining the relevancy of the domain. This results in the final curtaining to find 7,361 publications out of 8,431 total publications on ALD.
- Duplicate detection and elimination: there are possibilities of many forms of duplicates that are subjected to elimination. This mechanism is also controlled by inclusion and exclusion criteria. Two tasks were performed for this purpose: i) a different number of publications have been reviewed for another plant

leaf, e.g. corn, banana, grape, peach, potato, raspberry, tomato, strawberry, soybean, and orange to find that there is a total of 26,409 publications. This assists in further confirming is any form of overlapping common diseases in ALD and non-ALD research exists. ii) the second task is to find a list of papers that have addressed ALD either individually or by joint process towards the detection of apple scab, marssonina leaf blotch, cedar rust, spot, mosaic, fly speck, blotch, and rot. Finally, 7,135 papers have been shortlisted to confirm the accurate discussion of solutions to deal with these specific ALDs.

– Dual criteria: the inclusion criteria consist of i) selection of journals only, ii) paper published between 2018-2023, iii) should be related to implementation and not theoretical discussion or survey work, and iv) should have clear discussion of a set of methods used and clarity in results obtained. The exclusion criteria consist of non-ALD detection approaches only. Apart from this, inclusion and exclusion criteria also consider only the involvement of image processing and AI-based approaches.
– Secondary screening of articles: the secondary screening of articles is initiated by complying with inclusion and exclusion criteria, resulting in a total of 1,136 research articles from 7,361. This screening method involves an in-depth study concerning methodology, algorithm, and result implementation. This screening also consists of cross-verifying the applicability of one methodology over another or on different datasets. Further, secondary screening is carried out for 1,208 publications towards image processing-based solutions, 5,243 publications on machine learning-based solutions, and 2,086 for deep learning-based solutions. It is found that this search has led to results outside of prior collected papers, and hence, inclusion and exclusion criteria are further applied to finally obtain a confirmed number of publications that are discussed in this paper.
– Extraction of outcomes: the extraction of outcomes is in the form of a clear visualization of research trends, research gaps, and an understanding strength and effectiveness of reviewed journals.

The methodology took approximately 780 hours of involvement to arrive at the final list of unique and potential recent research methodologies using image processing and AI-based methods towards ALD diagnosis. The following section elaborates on the findings of existing methods.

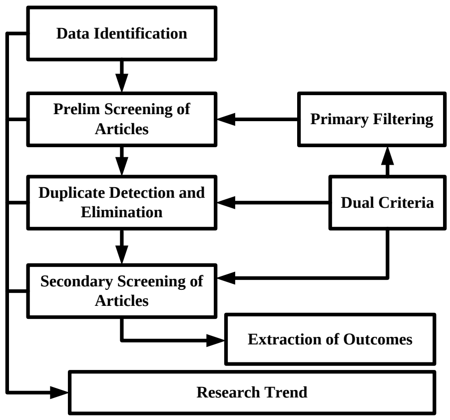

Figure 2. Adopted methodology

4. IMAGE PROCESSING-BASED APPROACHES

The discussed presented by Alqethami *et al.* [17] exhibits a combination of both machine learning and varied deep learning methods to carry out the identification and categorization of ALD. The study has particularly emphasized deploying a predictive classification approach on a standard Kaggle dataset without emphasizing prior steps before classification (i.e., image acquisition, preprocessing, and feature extraction). A study towards feature processing is carried out by Tian *et al.* [18], where the fusion process is carried out over multiple scales for an adequate representation of diseased spots. The prime notion of this study model is to address the challenges of detection associated with variable sizes of lesions.

Apart from this, various studies have been carried out towards adopting segmentation towards ALD, which performs distinct segregation of foreground to the background for effective detection. The problem towards segmentation is carried out by Li *et al.* [19], where semantic segmentation is introduced to facilitate extraction of lesion features. The study has used a network model that includes a spatial pyramid pool where the study models report high-performance modelling using transfer learning. Another segmentation-based problem solution was discussed by Storey *et al.* [20]. The presented study has used instance segmentation towards the identification of rust disease. Training is carried out using masked convolution neural network (CNN) models to detect and segment an object. Another unique segmentation method is presented by Khan *et al.* [21], deploying correlation-based method and evolutionary search-optimization approach. According to this concept, the images are subjected to preprocessing followed by feature extraction and classification.

The study uses a 3D median, Gaussian, de-correlation, and box filtering to enhance the leaf spots. Correlation and expectation maximization approaches carry out the segmentation process. The next part of the implementation fuses features associated with local binary patterns, colour histograms, and colour attributes. Finally, a support vector machine (SVM) and genetic algorithm have been used to optimize the features that contribute towards detecting and classifying multiple disease conditions of apple leaf. Another unique study towards the segmentation approach has been carried out by Hasan *et al.* [22], where wavelet transform and colour segmentation are combined to perform ALD detection. The technique uses a space-oriented colour segmentation approach to identify the leaf's infected region. The pixel classification towards the healthy and defected infected region uses colour markers and nearest neighbor methods. The primary feature is obtained using wavelet transform, while the secondary feature is obtained using a colour space histogram. Finally, the ultimate feature vector is obtained from fusing horizontal features. Finally, random forest (RF) based classifiers are utilized to perform multiple disease classification. Another unique study model is reported by Jiang *et al.* [23] using hyperspectral images of ALD, explicitly focusing on detecting a mosaic of apple leaves. The acquisition of an image is carried out by spectrometer, followed by the evaluation of the contents of anthocyanin. The study also constructs an optimal model of XGBoost to estimate the contents of anthocyanin, followed by using Gaussian wavelet transform for obtaining spectral reflectance correlation. The beneficial aspect associated with image-processing based disease detection techniques are simpler deployment [17], capable of detecting spots of different sizes [18], high-performance model [19], good accuracy [20], can detect scab, rust, and black rot [21], 98% accuracy, can detect cedar apple rust, black rot, and scab [22], and applicable for large-scale detection [23]. The limitation observed from studies are not emphasized data quality before applying the learning method [17], illumination fluctuation is not considered [18], analyzed over the smaller dataset, no benchmarking [19], aterative model [20], computationally intensive model [21], induces higher computation time and resources [22], and study model specific to mosaic disease [23].

5. ARTIFICIAL INTELLIGENCE-BASED APPROACHES

A joint method of AI using both deep learning methods and machine learning approach has been initiated by Bonkra *et al.* [24] towards detecting ALD. The discussion provides substantial evidence of various AI-based methodologies at present. Further, it is noticed that CNN is more used to identify ALD from AI-context solutions. Ahmed and Reddy [25] have introduced a CNN-based approach towards identification of ALD. According to this model, a unique interface is designed to be run on a smartphone, which captures the image and subject it to detection of different plant diseases. The system uses CNN to train standard datasets to classify multiple diseases. A similar work trend is also witnessed in the model presented by Bansal *et al*. [26], where CNN has been adopted in its ensembled form. The model classifies the leaves of an apple tree into multiple categories of diseases using EfficientNet and DenseNet pretraining methods.

Further work towards improving the precision of identifying ALD is presented by Gong and Zhang [27] using region-based CNN. The prime notion of this model is to address the challenges of complex background images. The feature extraction mechanism is formed as a network using the architecture of the pyramid network and Res2Net. The infection region is identified by region of interest, while the suppression technique is applied to narrow the detection ranges for higher precision. The adoption of a similar methodology of CNN and region-of-interest is also seen in the work reported by Yu and Son [28], where the work addresses the issues of discriminative power owing to frequent uses of attention mechanisms without considering spot region and background. Ding *et al.* [29] has used a dual attention-based scheme to perform the classification of ALD along with multiscale feature extraction.

Research by Li *et al*. [30] have mitigated the problems associated with imbalanced dataset towards the detection of ALD using CNN. The study model performs a comparative assessment of various CNN-based models to understand the better version, leading towards higher accuracy. The model presented by Yan *et al.* [31] is used for enhancing CNN towards rapid diagnosis of three specific cases of ALD. With a target of enhanced convergence speed, the model has used visual geometry group (VGG16), a 16-layered CNN pretraining model, while transfer learning is utilized to control the elongated training time. Research by Chao *et al.* [32] where DenseNet and Xception are integrated to formulate a deep CNN architecture. The uniqueness of this model is that it adopts global mean pooling and does not use fully connected layers of CNN, unlike conventional CNN implementation.

The features are extracted using a CNN model followed by categorizing disease forms in apple leaf by SVM. Adoption of CNN is also reported in Yang *et al.* [33], where EfficientNet is used along with a fusion of multistage feature. Di and Li [34] have addressed the problem associated with a complex form of leaf vein varieties that challenges the correct detection of ALD. Sharma *et al*. [35] have considered a location-specific variant of an apple where CNN is applied to construct a predictive model for ALD detection. Another unique implementation model constructed by Perveen *et al*. [36] has addressed the issues associated with the fluctuation of inter and intra-classes among features of apple leaf. Fu *et al*. [37] have used the AlexNet model to detect multiple disease conditions deploying CNN. Vishnoi *et al.* [38] have addressed computational training-related problems of deep learning-based approaches. Luo *et al.* [39] have constructed a fusion network of multiscale features towards better granular detection and classification of ALD. The model has used ResNet for better circulation of information, which is further boosted by rectified linear unit (ReLU) and normalization of batch information.

However, most existing studies have been conducted more in experimental mode and less in real-time environments. Jiang *et al.* [40] carry out a study towards this direction, which uses an enhanced version of CNN towards disease diagnosis. Zhu *et al.* [41] carried out further study toward early detection in real-time mode, which uses the inception model towards extraction features of multi scales associated with different variants of sizes of spots on apple leaves. Another study towards a real-time diagnosis of ALD using deep learning approach was discussed by Khan *et al*. [42].

Gao *et al*. [43] have carried out a study that presents a solution towards the complex background of images of ALD. According to this study model, a bilateral filter is introduced to preprocess the image to improve the texture and colour attributes. The existing study has also witnessed the use of principal component analysis (PCA) to assess ALD. According to the study model presented by Xing *et al*. [44], PCA has been used to improve the rating score for detection based on the distance of the central vein and imbalance degree. Further logistic regression analysis is used to optimize the detection outcome further. Another unique, a version is seen in the work of Ruth *et al.* [45], where bioinspired algorithms have been integrated with the learning approach. According to this study, the features are extracted by CNN, while the monarch butterfly optimization algorithm (MBOA) is used for optimizing the extracted features.

Specific categories of existing studies use state of an art AI-based object detection approach called you only look once (YOLOv5). Research by Zhu *et al.* [46] have used revised version of YOLOv5 by involving a module for improving feature for improving outcome data along with coordinated attention for improving detection efficiency. Further, enhanced semantic information is obtained by integrating pan and feature pyramids. An equivalent form of considering YOLOv5 was seen in work reported by Li *et al.* [47]. However, the methodology slightly differs from previous work. According to this implementation, an efficient extraction of fused features of multiscale is accomplished from the bidirectional feature pyramid.

A different variant of the YOLO module called YOLOX is also reported to be used in existing research, offering more simplicity and better performance. Research by Liu *et al.* [48] has used a discrete version of YOLOX with supportability of real-time detection of ALD. The limitation of the AI-based techniques are not emphasized data quality before applying the learning method [17], applicability is subjective to considered use-cases, narrowed evaluation scope [25], narrowed dataset-based investigation [26], only 63% of accuracy [27], fixed-architecture model with input size [28], accuracy is low [29], less number of images involved in the assessment [30], training consumes considerable time [31], not suitable for high-end and massive-sized data [32], demands potential computational resources for classification [33], computational burden due to multiple events of data replication [34], training consumes significant time [35], complex form of network [36], challenges towards model interpretation if different dataset is used [37], no benchmarking [38], induces computational complexity [39], susceptible to overfitting [40], higher computational cost [41], reduced classification accuracy [42], non-involvement of illumination attributes [43], slightly reduced accuracy performance [44], lack of inclusion of complex behavior modelling [45], demands high computational resources [46], narrowed scope of implementation in different scenarios of the dataset [47], and study applicability specific to the considered environment [48].

6. DATASET FOR APPLE LEAF DISEASE

The investigation towards the diagnosis of ALD is carried out via different forms of the available standard dataset. Such a form of dataset consists of various class-based information associated with the diseases of various plant leaves in a highly structured form. Various images are facilitated in different image formats to perform research-based studies. Briefing of these frequently used datasets is as follows:

– PlantVillage dataset: this is the most frequently used standard dataset that involves approximately 54,303 leaf images divided into 38 core classes concerning disease and species of plants [49]. They consist of both healthy and infected images. Further, this dataset is extended to 39 classes with 61,486 images by Pandian and Geetharamani [50]. This dataset consists of leaf images of apples, potato, pepper, peach, orange, grape, corn, cherry, and blueberry. Further, this dataset is also witnessed to be annotated using masked CNN style with a motive to higher accuracy in localization of infected regions [50]. However, the annotation is carried out for only cedar apple rust, apple scab, and black rot over 850 images.

– Plant pathology dataset: this dataset is also used for exclusively diagnosing foliar diseases in apple trees. It consists mainly of target label information maintained in CSV files, and train and test images. There are 3,642 image files in jpg format, used mainly to distinguish scab, rust, and healthy ones [51], [52].
– Apple leaf dataset: this is one of the recently developed datasets whose prime purpose is towards segmentation operation. The images were acquired from Northern China from the Northwest University of Agriculture, and interestingly, all the images have been captured from mobile phones. 51.9% of images bearing multiple disease conditions have been acquired from the laboratory, while 48.1% have been acquired from an accurate agricultural site in natural weather conditions. This dataset is used for investigating diseases, e.g., rust, brown spot, grey spot, and leaf spot [53].
– AppleLeaf9: this dataset is constructed by fusing multiple datasets, i.e., PPCD2021, PPCD2020, ATLDSD, and PVD. The conventional PVD consists of 54,306 images with 26 diseases [49], while PPCD is a dataset from plant pathology for two different years (2020 and 2021) of challenge obtained from Kaggle [6]. The ATLDSD is an apple leaf dataset used for segmentation. The dataset of AppleLeaf9 is practically meant to offer an analytically supportive test bed for applying CNN [33].

The dataset is prepared by Li *et al.* [19], which consists of 3024×4032 resolution apple leaf images captured from iPhone 13. There are 267 images, mainly classified into 152 ring rot images and 115 images of rust classes of diseases in jpg format. Colabeler V2.0.4 is used to annotate the dataset captured in uneven illumination conditions. The data were collected from the reputed agricultural institution in Shanxi. Similarly, another dataset has a similar form of resolution images captured from mobile phones in Baishui Apple Orchard of China with 6,268 labelled images with three classes of ALD [48].

7. RESEARCH TRENDS

The prior section has discussed the usage of different techniques of image processing and AI towards ALD detection. The discussion of the prior methodologies is restricted to only recently published articles, whereas there are various archives of studies carried out in this segment. As a continuation of our prior work [54], it is noticed that there is approximately 1,052 unique research implementation on average, as noticed from the observation-based values in Table 1.

Table 1. Total publication for apple leaf detection and classification

Publishers	Number of papers
IEEE	10
MDPI	48
Springer	4384
ACM	20
Taylor & Francis	10
NCBI	287
ScienceDirect (SD)	2602

Table 1 shows that the number of unique implementations varies from one place of publication to others. The values for several papers are taken for the publication duration of 2018-2023, and it's restricted to journals only. A total of 7361 journals have been noticed to be published in this due course of considered time. Apart from this, it is to be noted that this number is confined only to research implementation associated with apple leaf. In contrast, the bulk of research work is carried for another leaf from different crops and fruits, as exhibited in Table 2.

Table 2. Total research work done on plant disease

Other leaf	IEEE	MDPI	Springer	NCBI	SD
Corn	2	8	1577	127	1236
Banana	0	3	943	40	516
Grape	4	9	1318	74	950
Peach	0	1	695	23	409
Potato	0	16	3288	282	1854
Raspberry	0	0	305	19	249
Tomato	5	48	3597	269	2371
Strawberry	2	8	854	36	576
Soyabean	0	0	49	27	24
Orange	2	4	2713	84	1792

From the observed values of Table 2, it is noted that there are 26,409 journal publications with different reputed publishers of scientific articles related to different types of plants as well. From this observation, it can be said that research work considering apple leaf for disease detection is considerably less than other leaf disease detection. As mentioned earlier, a closer observation of each approach for such a plant's leaf is found to address various specific diseases. This evidence clearly states that research towards ALD is a new beginning and still has a long way to go. Moreover, it will be too early to state that approaches used for other plant-based leaf disease detection will work with a reliable success rate with ALD detection. This is because diseases and their characteristics for each plant differ, while there are some fair possibilities of re-utilizing some of the approaches for ALD as well. The following research trend is emphasized on the number of research work towards specific forms of ALD as noted in Table 3.

Table 3. Total research work done on specific apple leave disease

ALD	IEEE	MDPI	Springer	NCBI	SD
Apple scab	2	36	413	84	324
Marssonina leaf blotch	1	4	27	6	21
Black rot canker	1	4	703	19	664
Collar rot	0	2	82	5	35
Sooty blotch and fly speck	2	4	233	26	108
Apple mosaic and other virus diseases	2	8	774	32	382
Alternaria leaf spot	6	17	1877	95	1029
Apple cedar rust	2	3	60	3	39

The numerical scores shown in Table 3 state that 7,135 research journals are being published where a more significant number of works towards ALD is carried out towards investigating leaf spot (3,024 journals) followed by black rot canker (1,391 journals) while much smaller number of research work is carried out towards leaf blotch disease in ALD (59 journals). These tabulated scores of observations suggest that there are uneven forms of consideration towards finding solutions for only a few numbers of ALD while the rest of other diseases (e.g., leaf blotch, apple cedar rust, and scab) are still less explored. It should be noted that these ALDs are pretty standard irrespective of any geographical region, given their cause of origination. The existing research community is witnessed to adopt image processing-based methodology towards ALD detection, as shown in Table 4. This is one most frequently adopted technique that is easier to acquire with an available standard dataset as mentioned in the previous section.

Table 4. Image processing techniques used for ALD detection

Publishers	IEEE	MDPI	Springer	NCBI	SD
Segmentation	1	3	245	6	232
Region of interest	0	0	1198	11	294
Preprocessing	0	0	0	0	0
Feature extraction	6	6	567	10	336
Classification	6	5	668	12	517

Table 4 shows that region-of-interest (n=1,503 journals) and classification approach (n=1,208 journals) are the most frequently adopted image processing schemes. However, maximum number of schemes towards classification are seen to use learning-based methodology to perform accurate identification. Another outcome of this observation is that no unique research is being reported to adopt a preprocessing-based approach as the core study goal towards ALD detection, while the core segmentation-based approach is also not reported to be used extensively (n=487 journals). Further feature extraction is slowly gaining pace in solving the ALD detection problem (n=925 journals). However, not much unique study implementation is observed compared to classification approaches. This is because classification approaches carried out via various learning algorithms (e.g. CNN) are independent of feature extraction; however, this fact doesn't justify the accuracy being accomplished. Feature engineering of image signals will always remain a prime importance to deal with various complications of low and high-level features that are adversely affected by large sizes of data, fluctuation in illumination conditions, and complex background problems. These problems are not reported to be sorted out by core image processing approaches. Therefore, on the ground of this data in Table 4, it can be stated that a smaller number of pure image processing approaches are witnessed in ALD detection. The following observation towards research trend is carried out towards adopting another frequently adopted methodology, i.e. AI towards ALD detection. For this purpose, the study captures separate scores for its learning-based approaches-based approaches, as noted in Tables 5 and 6, respectively.

Table 5. Machine learning-based AI techniques used

		Publishers	IEEE	MDPI	Springer	NCBI	SD
Supervised learning	Classification	Naïve Bayes	0	0	42	0	47
		Decision tree	0	0	462	4	266
		SVM	4	4	361	3	281
		RF	0	1	338	0	298
		K-nearest neighbor	0	1	128	0	116
	Regression	Linear regression	0	1	541	0	433
		Support vector regression	0	2	277	0	150
		Decision tree regression	0	0	195	0	123
		Lasso regression	0	0	21	0	10
		Ridge regression	0	0	43	0	17
Unsupervised learning	Clustering	K-means clustering	0	0	146	0	344
		Agglomerative hierarchical clustering	0	0	10	0	9
		Gaussian mixture	0	0	63	0	34
Reinforcement learning	Decision making	Q-learning	0	0	3	0	94
		R-learning	0	0	0	0	371
		TD-learning	0	0	0	0	0

Table 6. Deep learning-based ai techniques used

Publishers	IEEE	MDPI	Springer	NCBI	SD
Convolutional neural networks	2	9	205	10	267
Long short-term memory networks	0	0	49	0	19
Recurrent neural networks	0	0	100	0	40
Generative adversarial networks	0	0	54	0	36
Radial basis function networks	1	0	116	1	52
Multilayer perceptron / artificial neural network	7	1	350	1	245
Self-organizing maps	0	0	323	0	26
Deep belief networks	0	0	106	0	21
Autoencoder	0	0	32	0	13

Tables 5 and 6 show that there are a greater number of implementation work of machine learning-based scheme (n=5,243 journals) compared to that of deep learning schemes (n=2,086 journals). From the context of machine learning schemes in Table 5, it is seen that extensive research work has studied the applicability of linear regression (n=975 journals). At the same time, other associated accompanied approaches are decision tree (n=732 journals), SVM (n=653 journals), and RF (n=637 journals), while not much work is carried out using unsupervised machine learning schemes. From the context of deep learning-based approaches witnessed in Table 6, the researchers have widely adopted the CNN approach (n=493 journals), while the next is the multilayer perceptron-based approach (n=604 journals). There is something more to observe from the numbers shown in these tables and the unique implementation. The number of publications using machine learning is slowing down while deep learning approaches (specifically using CNN) are gaining pace among researchers. Apart from this, there are various studies where multiple algorithms of machine learning or deep learning have been jointly used, making it more challenging to realize the unique implementation of any learning approach to ALD detection. However, one common observation is that CNN has found many research publications towards ALD detection, considering multiple use cases of leaf diseases in apples. Therefore, the learning outcome of research trends can be summarized as follows: i) there are considerably fewer research publications specifically towards ALD detection than other plant-oriented leaf disease detection, ii) from the perspective of ALD, the widely researched methodologies have considered the detection of leaf spots to be the highest number, while studies on rot and mosaic are also gaining in their pace for adoption, iii) from the perspective of image processing-based approaches towards ALD, it is noticed that region-of-interest-based schemes and classification-based schemes are highly investigated research areas. At the same time, there is no attention towards the preprocessing-based approach, iv) feature extraction and segmentation, the most critical operational steps of image processing-based approaches, have not witnessed many more publications towards ALD specifically, v) from an AI perspective, it is noticed that machine learning approaches are significantly more in publication as compared to deep learning approaches. However, unique and individual machine learning approaches are less witnessed, while most use ensembled versions, vi) from a machine learning perspective, more work is carried out considering classification-based supervised algorithms compared to regression methods towards ALD. Less emphasis is found towards unsupervised and reinforcement learning approaches, and vii) from the perspective of a deep learning-based approach, CNN and its different variants using pretraining methods have been dominantly adopted towards ALD detection. Although this states the higher likelihood of success rate using CNN, other similar potential approaches like long short-term memory and autoencoder have not been evaluated much.

8. RESEARCH GAP DISCUSSION

The current manuscript reviews the strengths and weaknesses of frequently deployed image processing and AI-based methods. Hence, the research gap becomes the actual outcome of the contribution of the proposed review work. The review of recent scientific journals associated with solving ALD detection problems shows that various methodologies have emerged. These existing methodologies have addressed the common problem of ALD detection considering variable disease conditions. However, a few emerging issues have not been reported to be addressed, which is a missing research gap. Based on the observation, the following are some essential research gaps:

– Generalized challenges of ALD not addressed: various diseases with different names can have overlapping symptoms, which makes it challenging for the system to undertake reliable and accurate detection. Further, the outcome of existing methodologies cannot confirm the originating reason for the diseases. Wilting or lead discoloration can be caused by various reasons, which are hard to distinguish. It is also noted that symptoms of ALD are temporally evolved; hence, early-stage detection is quite challenging and often yields outliers.
– Less emphasis on illumination variability: none of the existing research has emphasised considering the impact of illumination conditions, which could significantly affect real-time computation. The positioning of leaf, camera settings, artefacts, occlusion, blurriness, noise, and lighting conditions are not much emphasized; moreover, the availability of annotated data by experts is relatively less available. However, such issues can be sorted out to some extent by a dedicated preprocessing model, which is again found missing in any existing methodologies.
– Reduced target to minimize complexity: most of the problem solution for ALD is based on deep learning in AI, which is not only iterative but also demands extensive resources for obtaining high-accuracy detection and classification. None of the existing approaches has worked towards exploring the scope of optimizing the computational performance, nor has it sought a balance between computation and accuracy demands simultaneously.
– Lesser evidence towards real-time processing: almost all the existing studies have been carried out by publicly available datasets or constructed their dataset to testify to the model's accuracy. However, such testing is not carried out on a large scale in real-time processing, which demands the algorithm to be distributed and robust, along with the supportability of parallel processing. Handling a massive dataset from an apple orchard is not feasible without this. Further, high detection accuracy must be effectively balanced with low-latency processing, which demands optimization.
– No evidence towards interpretability: it is witnessed with evidence that CNN and its associated variants are one of the dominant deep learning methods deployed for ALD diagnosis. However, it is characterized by complex architecture and often features black box attributes. The actual interpretation by deploying CNN over a large heterogeneous dataset has a higher likelihood of non-linearity, and high-level abstraction poses an interpretability challenge. The better option is adopting an attention mechanism for effective decision-making, which is seen in a smaller number of implementations.
– Limitation of available dataset: the available dataset of ALD is quite effective in the primary stage of investigation and in designing a preliminary framework towards ALD. However, this dataset lacks any information about rare diseases in apple leaf and is only limited to spots, rust, blotch, and mosaic. Such issues can be investigated via generative model, transfer learning, and data augmentation, which are not currently available in the literature.
– Tradeoff-between image processing and AI: a closer look into existing studies shows that pure image processing-based ALD detection is significantly less compared to AI-based methods. It is also seen that AI-based methods consider involving image processing steps before applying different variants of AI algorithms. However, the involvement of image processing in AI is not reported to reduce the computational burden of iterative schemes of AI. Neither are they reported to offer cost-effective solutions. With massive image processing algorithms in different use-case scenarios, the applicability of ALD is significantly less. Hence, no proper balance between image processing and AI-based approach is observed to jointly improve accuracy and cost-effective computational operation equally.
– Remarks: based on insights into the overall outcome of this review work, it can be noted that both image processing and machine learning-based methods are beneficial towards diagnosis of ALD; however, it demands serious planning of practical implementation. The prominent reason for issues found in existing

schemes is mainly due to the dataset, as they lack a single scene of a leaf under variable lighting conditions, angles, and stages of disease progression. Hence, dataset quality must be improved to carry out a reliable predictive operation, where data augmentation and preprocessing schemes will be pretty helpful. Although CNN has reported issues of computational resource demands, they significantly contribute towards capturing essential patterns and characteristics of leaves only if they are used in deep learning mode, i.e., deep CNN. Apart from this, it is necessary to address a maximum of the research gap mentioned to evolve into a better predictive diagnosis model for ALD.

9. CONCLUSION

This paper has discussed recent techniques associated with image processing and AI-based methods to diagnose ALD effectively. The primary novelty of this research work is that this is the first elaborated survey with more profound insights into potential methodologies in the present era of publications. This paper's secondary novelty can be presented as learning outcomes as follows: i) the symptoms exhibited in ALD in apples are sometimes entirely overlapping, and it is pretty challenging to discretize them owing to the absence of any image-based statutory reference. This overlapping symptom and multiple causes resulting in similar symptoms are some of the core hurdles existing research models could not find answers to. ii) with the progressive advancement of image processing algorithms, conventional object detection algorithms cannot solve the complications in detecting accurate symptoms in ALD. Region-of-interest is reported to be the most suitable method, and it is frequently adopted by existing researchers too. iii) the number of core methodologies of image processing-based solutions is much less than AI-based methods (although they also use image processing-based methods). The alarming observation is that there is no reported preprocessing-based framework to deal with already known complications of near real world or real-time images. iv) the deep learning algorithm's usage is much lower than machine learning algorithms, as noted in double the size of its publications. However, the adoption of deep learning-based schemes is consistently higher, with more researchers adopting CNN and its variants to solve ALD detection problems. v) compared to the area of detection and classification of an object, the experiments carried out have witnessed relatively lower accuracy scores. Still, investigations on ALD have a long way to go compared with the exponentially higher number of work models in other leaf disease detection algorithms. And vi) currently, no benchmarked model is being reported with a feature of equal accomplishment of accuracy and low computational complexity. No real-time-based experimentation has been used for final validations. There are studies where real-time images have been used for constructing datasets, but the model trained on that dataset has not been analyzed extensively. Hence, there is only 20% approximate progress in ALD diagnosis, which demands more in-depth investigation. Therefore, future work will be in the direction of mitigating the identified issues. The first direction of work can be carried out emphasis on addressing primary challenges associated with leaf images using a novel preprocessing algorithm. The second direction of work could be further to experiment with equal emphasis on all AI-based approaches to seek optimal solutions. The idea is to balance the higher accuracy demands with lower computational cost with higher applicability in a real-time environment.

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