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SURVEY

A Systematic Literature Review of Machine Learning Techniques Deployed in Agriculture: A Case Study of Banana Crop

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ABSTRACT Agricultural productivity is the asset on which the world’s economy thoroughly relies. This is one of the major causes that disease identification in fruits and plants occupies a salient role in farming space, as having disease disorders in them is obvious. There is a need to carry genuine supervision to avoid crucial consequences in vegetation; otherwise, corresponding vegetation standards, quantity, and productiveness gets affected. At present, a recognition system is required in the food handling industries to uplift the effectiveness of productivity to cope with demand in the community. The study has been carried out to perform a systematic literature review of research papers that deployed machine learning (ML) techniques in agriculture, applicable to the banana plant and fruit production. Thus; it could help upcoming researchers in their endeavors to identify the level and kind of research done so far. The authors investigated the problems related to banana crops such as disease classification, chilling injuries detection, ripeness, moisture content, etc. Moreover, the authors have also reviewed the deployed frameworks based on ML, sources of data collection, and the comprehensive results achieved for each study. Furthermore, ML architectures/techniques were evaluated using a range of performance measures. It has been observed that some studies used the PlantVillage dataset, a few have used Godliver and Scotnelson dataset, and the rest were based on either real-field image acquisition or on limited private datasets. Hence, more datasets are needed to be acquired to enhance the disease identification process and to handle the other kind of problems (e.g. chilling injuries detection, ripeness, etc.) present in the crops. Furthermore, the authors have also carried out a comparison of popular ML techniques like support vector machines, convolutional neural networks, regression, etc. to make differences in their performance. In this study, several research gaps are addressed, allowing for increased transparency in identifying different diseases even before symptoms arise and also for monitoring the above-mentioned problems related to crops.

INDEX TERMS Machine learning, banana, diseases, imaging, classification, ripeness, hyperspectral.

I. INTRODUCTION

The banana plant described as *Musa sp* (Musaceae family) is the second vital cultivation in India succeeding the mango [1]. Its complete year sustainability, cheap price, diverse range, flavor, nourishment, and remedial value place it as

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a best-loved fruit among the communities. The fruit originates from the soupy tropical areas of South East Asia with India. *Musa acuminata* and *Musa balbisiana* [2]- are the two varieties from which contemporary consumable forms have evolved. During the 7th century AD, the cultivation of bananas broadens to Africa and Egypt. Currently, its cultivation fills out nearly all the hot tropical areas of the globe between 300 N and 300 S of the equator. *Musa paradisiaca* [3]

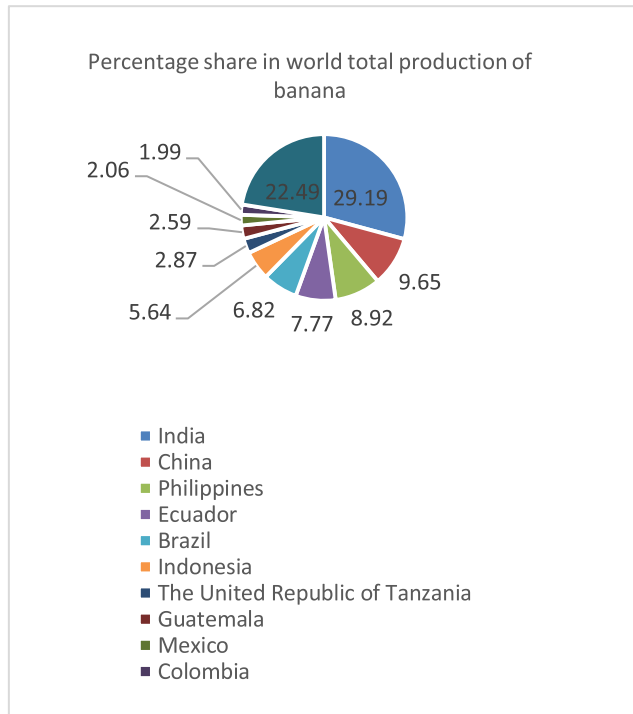


FIGURE 1. Percentage share in world total production of banana [1].

is cropped in about 120 nations. The percentage share of bananas in world total production is approximated as 86 million tons of fruits as shown in Fig. 1 India participates in the total banana production with a yearly output of nearly 14.2 million tons. India, China, the Philippines, Ecuador, Brazil, Indonesia, The United Republic of Tanzania, Guatemala, Mexico, and Colombia are some major producers of bananas in the World [1].

Bananas are cropped out at a very matured green phase and they continue to be green and hard without notable difference in peel color and texture before ripening begins. Once the ripening process starts, it turns out to be irreversible and incorporates chemical changes and texture changes. The ripening process of banana fruits is progressively carried out using some experimental methods by trained people. Different techniques have been utilized to check the shelf-life phases of the fruits but adopted methods are destructive. The fuzzy logic controller has been used to classify the hundreds of samples of bananas into various categories of ripeness [4]. Another fuzzy logic approach is used to determine the progression rate of banana ripeness and determine the shelf-life of banana fruit [5]. Model extracted ethylene gas content and ambient temperature for ripeness evaluation. In the paper [6], banana ripeness states and shelf-life were measured using k-means and a decision tree learning classifier.

During the export and import process of the bananas, fruits need to be reserved in a cool place to assure their quality, so that their condition would not be degraded on reporting at the destination. Bananas show chilling injury symptoms just when kept in cold storage at 10°C which could deteriorate

the fruit quality [7]. Discoloration of fruits occurred on the injured place of fruit, skin color turned to brown, or black depending on the seriousness of the injury. The severity and appearance of chilling injuries are affected by time, temperature, and the ripening phases of the fruits.

Additionally, bananas are also affected by many kinds of diseases and infections like Banana Streak Virus, Moko disease, Sigatoka disease, Bunchy Top Virus, etc. In [8], the k-nearest neighbor (KNN) classifier was used to detect disease in banana leaves with an overall accuracy of 96.87%. In another approach, a convolution neural network (CNN) is operated over 5167 images and formed a disease detection system [9]. “Banana Sigatoka, Banana Cordial Leaf Spot, Banana Diamond Leaf Spot, and Deightoniella Leaf and Fruit Spot” disease detection & classification are carried out in [10]. There is also a need to detect these ailments and their primary manifestations. To protect the quality and quantity of bananas, farmers need to find the diseases present either in the fruit or plant of bananas. Normally, identification is carried out either by the manual, visual, or microscopic process. The difficulty with visual evaluation is that being an intuitive function, it is susceptible to intellectual and cognitive experience that may cause bias. On the contrary, laboratory analysis approaches are often time-consuming and lack to give responses on time. In the state of affairs, it is demanded to emerge automatic systems proficient in classifying diseases in a fast and authentic way.

Generally, this is very restricted for practical applications, due to the range of pathogens that can simultaneously spread a disease to a banana plant or fruit and originate disease manifestations is normally higher.

To address the difficulties; the intricate and multivariate agricultural systems should be better comprehended by persistently monitoring, estimating, and analyzing using different physical perspectives and phenomena. This suggests scrutiny of huge agrarian information [11], and the applicability of new data and correspondence advances (ICT) [12], both for short as well as for bigger scale biological systems’ perception. Larger scale perception was encouraged by remote detecting [13], performed using satellites, planes, and unmanned airborne vehicles (UAV) (such as drones), giving large previews of the agricultural situations. Most of the procedures explained in the literature are rooted in digital images of manifestation either in visible or near-infrared bands [14]; these bands are reviewed in isolated or regarded in multi and hyperspectral imaging (HSI). The simultaneous collection of spatial images in numerous spectrally contiguous bands constitutes the complicated, highly interdisciplinary field known as HSI [15]. The hyperspectral image has a full spectrum for each pixel. As a result, HSI is a very potent method for characterizing and evaluating agricultural productivity. The incorporation of spectrophotometry and imaging techniques for uncovering hidden information non-invasively for direct detection of specific components and their spatial extent is the driving force behind the development of HSI systems in food quality evaluation. In order to capture morphological data

from agricultural product samples, HSI represents a significant technological advancement [16]. Many researchers have employed the HSI techniques with or without the combination of Machine Learning (ML)/ Deep Learning (DL) for various agricultural applications [17], [18], [19], [20]. The most prominent techniques adopted for analyzing images using ML are K-means, CNN, artificial neural networks (ANN), support vector machines (SVM), linear polarization, vegetation indices (e.g. NDVI), regression analysis, and wavelet-based filtering. Moreover being an extension to ML with more network depth, DL models especially, CNNs are more flexible and adaptable for a wide variety of very complicated applications [21]. Apart from the agriculture, Robotics [22], [23], Autonomous detection of damage [24], [25], Medicine [26], [27], etc. are some challenging applications where DL works well and their highly hierarchical structure and strong learning capacity enable these to do classification and predictions very effectively.

The motivation for setting up the review comes from the way that presently there exists many research endeavors utilizing artificial intelligence to discuss different farming issues in bananas with acceptable outcomes urged the authors to set up the review. Furthermore, this study has identified research gaps in terms of getting a clear and concise perspective of defects and diseases associated with crop health. The objective of the review is to have some detailed discussion on the banana with some of the challenges in disease classification, ripeness level monitoring, etc., to traverse in-depth, the causes and effects of the implementation of the techniques suggested so far.

To meet the target, research interrogations (RIs) are formed and comprehensive outlines are instigated. The aim of this study is to investigate the contemporary research trends in agriculture for bananas using ML techniques. The main contributions are highlighted as:

- A detailed investigation of ML techniques deployed to investigate the banana plant health in all aspects such as diseases, defects, ripeness, chilling injuries, moisture, etc.
- Discussions about the data collection process (image acquisition) and programming interfaces used to handle the tasks.
- Description of the extrinsic and intrinsic factors that affect the health of the crops.

The rest of the article is structured into the following sections: Section 2 explores the review procedure. Section 3 describes comprehensive planning of the review that comprises keywords hunt, up raising the RIs, and extraction of research papers. Section 4 explores the activities carried out while directing the survey that comprises the amalgamation of information. Reviews along with their answers are reported in the same. Section 5 gives an overview of some research perspectives discussing the current scenario and loopholes in it and shows some future research directions to improve the fruit quality and measure; finally, Sec. 6 concludes the review.

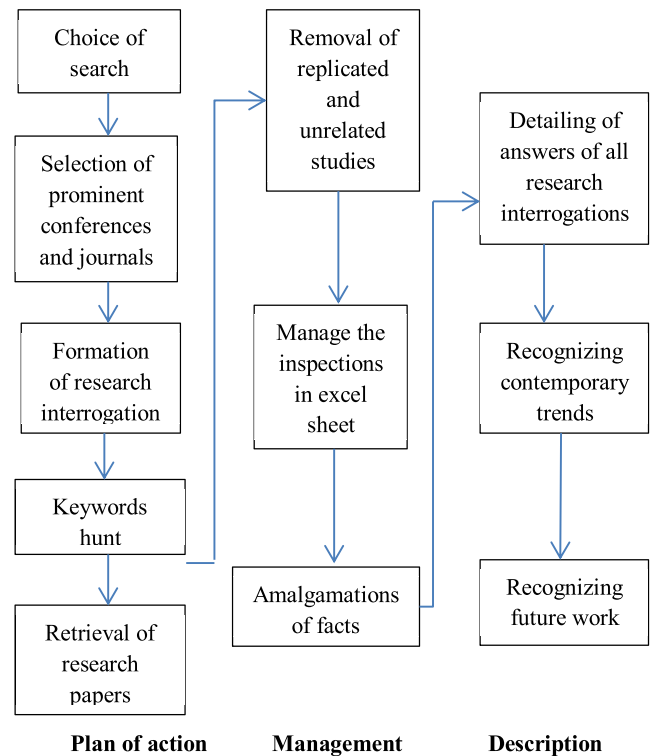


FIGURE 2. Review methodology.

II. REVIEW METHODOLOGY

The following segment clarifies the method of governing the consistent review embraced in the investigation. As portrayed in Fig. 2, the review strategy acquired in the examination is separated into three phases: the plan of action, management, and description. During the plan of action, search data sets were recognized, and then after the fundamental inspection, RIs were detailed. In the subsequent stage, all replicated and unrelated investigations were expelled, and preselected articles were sorted out. The amalgamation was also conveyed during this phase based on the data given in each of the shortlisted papers. Then later, responses to each reporting question were accounted for, and ongoing developments in every subfield were recognized. An attempt is also made to spot the limitations present in each study, which would make us move on the path of future research.

A. DETAILED PLANNING FOR REVIEW

1) CHOICE OF SEARCH DATABASES

The authors have started a hunt with the college site asset and EBSCO revelation administrations given by GGSIP University. The investigation procedure was cultivated in two phases. In the initial step, a watch word-based query was set to get a huge number of outcomes. In this procedure, Google Scholar, Web of Science, Scopus, ACM Digital Library, Springer, IEEE Xplore, Wiley, Science Direct, and Compendex were identified. In the subsequent phase, distributions over the significant journals and conferences were identified. The hunt is confined from 2009 to 2021 in particular.

TABLE 1. Research interrogations (RIS).

RI 1: What kind of commercially cultivated banana varieties are there and what kind of diseases may occur (either in banana plant or fruit)?

RI 2: What are common symptoms of diseases that occur in bananas and which parasite originates that disease?

RI 3: How the data has been collected for the precision agriculture of bananas? (tool, framework, and dataset used)?

RI 3.1: What programming interfaces have been used for implementation?

RI 4: What kind of images has been captured for analysis (RGB, Hyperspectral)?

RI 5: Which ML techniques have been used for banana disease detection, moisture content detection, ripeness monitoring, and other related problems?

RI 6: What kind of performance metrics have been used to measure the extracted features in our studies?

RI 7: How have been DL models implemented with or without visualization techniques?

RI 8: How is individual prediction used to evaluate the ML algorithm and what is the best-fitted model (Wherever applicable)?

RI 9: How do extrinsic and intrinsic factors affect the identification process?

2) SELECTION OF PROMINENT JOURNALS AND CONFERENCES

During the process of searching and accomplishing the desired target in minimal moves, it is required to pick suitable search databases. Certain viewpoints need to be considered in the choice criterion of search databases [28]:

- Search databases need to be renowned and authoritative to accommodate scholarly articles and to achieve the related and expected search outcomes.
- Search databases are aimed and straightly directed toward the needed research articles.
- Search databases accommodate advanced finding facilities such as refinement of articles up to certain levels.

The basis for the selection of significant journals and conferences in the said area in the survey also incorporates the range of references (citations), or the standard of the editorial board. Conferences and journals selected for review in the related area of disease detection and ripeness monitoring (particularly for banana plant fruit or leaves) alongside their aspects are outlined in Table 1.

3) FORMATION OF RIS

The subsequent stage was to bring up certain RIs to recognize the state of the art and the extent of future research. The cautious choice of RIs is significant as it follows us throughout our investigation to miss out or be digressed off-track while exploring tremendous data and distinguishing the corresponding data from the selected papers. Table 1 shows the rundown of significant RIs reported in the review.

TABLE 2. Quality assessment parameters (QAP).

QAP 1: Does the study focus on the main research problem?

QAP 2: Does the study define the need for the review?

QAP 3: Does information gathering methods clearly defined?

QAP 4: Does the study deploy any ML technique?

QAP 5: Does a correct and applicable literature review carried out?

QAP 6: Does the investigation have predictable and sufficient references throughout the years?

QAP 7: Does the study make use of suitable evaluation measures?

QAP 8: Does the study uses prediction models & show the best performing technique?

QAP 9: Does the study give clear results?

QAP 10: Does the study can define the limitations and scope of research in the domain?

4) KEYWORDS HUNT

While directing the deliberate survey, a keyword hunt for the systematic review was planned using a few steps [28]:

1. Extract the dominant search words from RIs.
2. Selecting the keywords from the abstract of relevant research papers.
3. Apply Boolean OR & Boolean AND to develop search parameters from the search keywords.

As inquiry watchwords, the authors have used the underlying question: [**“Machine learning”**] AND [**“Banana Disease”**, **“Banana classification”** OR **“Banana disease detection”**] OR **“Banana ripeness detection using machine learning”** OR **“Banana disease using deep learning”**.

5) RETRIEVAL OF RESEARCH PAPERS

All significant research papers were redeemed through corresponding digital libraries. Throughout the procedure, the citation part of each paper was additionally investigated to get related research papers/reports which were additionally recovered and sorted out for review.

III. REVIEW MANAGEMENT

During the direction of the systematic survey, all papers were contemplated completely and reported against the RIs as accumulated in Table 2. Requirements and restrictions present in shortlisted papers were likewise distinguished and arranged which give guidelines for future research work. A detailed amalgamation of the information occurred in this stage. The authors have put a conditional criteria dependent on RIs and keep examining each research paper using the previously mentioned criteria.

A. REMOVAL OF UNRELATED STUDIES

All the shortlisted papers were planned in sequential form, so the replicated papers could be promptly distinguished and

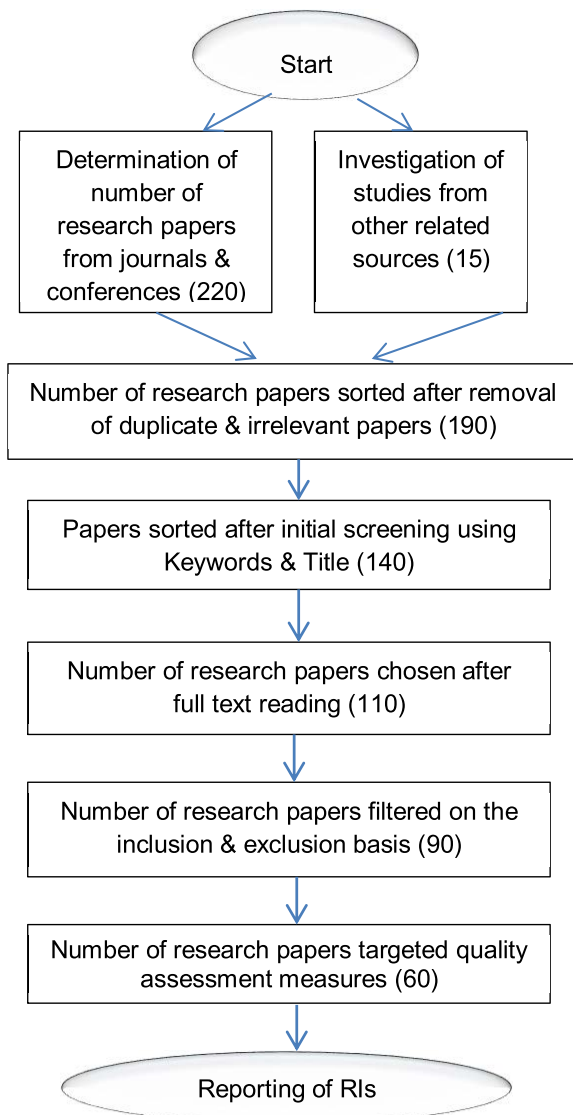


FIGURE 3. The flow of primary research papers selection.

expelled. Furthermore, the matter of the studies was properly examined and unimportant studies were expelled. The flow of primary research papers selection is shown in Fig. 3. A huge number of results got from the initial browsing phase and to remove the irrelevant studies, the authors have followed an Inclusion and exclusion criteria drawn straightforwardly from the RIs.

1) INCLUSION BASIS

- Research papers must target the banana (fruit/leaves) and surely answer any of the RIs.
- Studies use ML techniques to implement the system.
- Studies must have been written in the English language.
- Papers have to be peer-reviewed.
- Studies compared the performance of prediction models (wherever applicable).
- Papers should not be repeatable.

2) EXCLUSION BASIS

- Studies that do not target the banana plant and do not answer any of RI's.
- Studies not implemented using ML techniques.
- Papers are not written in the English language.
- Papers that do not cover the full length.
- Papers that are out of time -frame.
- Conference papers if a journal version of the same is available.

B. DATA EXTRACTION

“Place for everything and everything would be in place” as expressed by the popular administration Master Charles A. Goodrich was taken as a core principle to compose all shortlisted research papers for simple & snappy access and recovery before setting up the phase for directing such a broad review. The authors have arranged a database containing different properties, for example, authors' name, article name, publication date, the wellspring of productions(journal/conference/book/articles), watchwords, abstract of the studies, and comments. No document was put up without making a record in the database. The authors have seen this model as truly agreeable. Data present in every paper was carefully studied to discover the appropriate responses of all RIs. The authors have used different perception ways, for example, line diagrams, pie graphs, bar outlines, and so on to arrange different techniques, models, and performances in the present investigation.

A scoring criterion is set to check the quality assessment parameters outlined as follows: 1 indicates “Yes”, 0.5 indicates “Partially”, and 0 indicates “No” Scores are ranked in four classes: Excellent ($13 \leq \text{ratings} \leq 15$), good ($9 \leq \text{ratings} \leq 12.5$), fair ($5.5 \leq \text{ratings} \leq 9.5$), and fail ($0 \leq \text{ratings} \leq 5$). After assigning these ratings, 15 studies were excluded from the total papers. Finally, a total of sixty research papers are selected for conducting the systematic literature review.

C. RESEARCH PAPERS DISTRIBUTION

A study of explored or shortlisted research papers pinpoints that research trends for bananas are not uniformly distributed against the defined period (2009- 2021). All the shortlisted investigations were separated into three sections according to their source of publication, for example, journal publications, conference publications, and others that incorporate book parts, specialized reports, symposiums, etc. Fig. 4 portrays the dispersion of the papers according to the two classes. The percentage share of journals publication is 60% and conferences are with 40% contribution.

D. SELECTION OF PRIME STUDIES

In this systematic literature review, sixty base papers are there chosen to evaluate and compare the studies in banana disease prediction, classification, ripeness, and shelf-life indication domain.

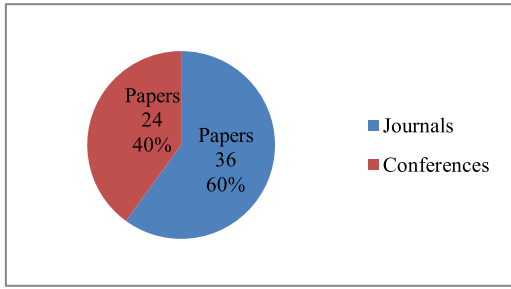


FIGURE 4. Division as per the source of distribution.

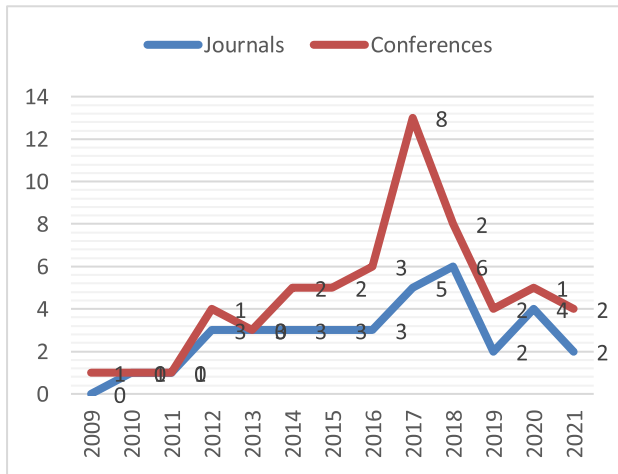


FIGURE 5. Year-wise distribution of papers.

E. YEAR OF PUBLICATION

The dispersion of years for all the shortlisted papers from the year 2009 to 2021 is depicted in Fig. 5. It seems apparent that the research on banana fruit quality prediction and disease detection has been very steady throughout the years. As of now, enthusiasm for nature-inspired techniques named evolutionary techniques has additionally been seen because of their undeniable result points.

IV. REVIEW REPORTING

The authors have inspected all shortlisted research papers of the last decade gathered from journals, conferences, symposiums, etc. in the field of banana disease detection, classification, and ripeness indication using ML with a means to explore answers to all the RIs portrayed in Table 1. The accompanying sub-areas present condensed facts and answers to all RIs.

A. RI 1: WHAT KIND OF COMMERCIALY CULTIVATED BANANA VARIETIES ARE THERE?

Economically, bananas are categorized either as dessert type or culinary type. The culinary type fruits are usually starchy in nature and these are used as vegetables in unripe mature forms. Major banana breeds incorporate Dwarf Cavendish, Nendran, Robusta, Red banana, Grand Naine, etc. Grand

Naine, a variety sourced from Israel is acquiring vogue and in the future become the most popular variety because of its forbearance to stress and superior quality bunches. A variety-wise yield of bananas along with the characteristics is given in Table 3.

B. RI 2: WHAT KIND OF DISEASES MAY OCCUR (EITHER IN PLANTS OR IN BANANA FRUIT)? WHAT ARE COMMON SYMPTOMS OF DISEASES THAT OCCUR IN BANANA VARIETIES AND WHICH PARASITES ORIGINATE THOSE DISEASES?

The manifestation in plant disease severity might be caused by some biotic factors such as fungal, bacterial, viral pathogens and abiotic elements such as weather, nutrient deficiencies, fertilizers, and soil issues. Many times, the reason for the symptom is not self-evident. Nearby assessment and research laboratory culture and analysis are required for the appropriate diagnosis of the causal operators of infection. Usually, fungal diseases issue noticeable indications with uneven growth, color, and patterns. Pathogens attack can also be seen in the form of fungal growth, bacterial ooze, etc.

1) INVESTIGATION OF BANANA PLANT DISEASE AND THEIR SYMPTOMS






The banana plant could be infected with a variety of diseases causing pathogens (fungal, bacterial, or viral) and infect the crop with Panama wilt [29], Sigatoka [30], Anthracnose [31], Tip-over [32], Bunchy top [33], Mosaic [1], Streak virus [34], etc. diseases that destroy the crop very severely in a short time. Some common symptoms of fungus, bacteria, and viruses in banana plant leaves and fruit are shown in Table 4 and their infected images are displayed in Fig. 6. The diseased images are taken from the AESA-based IPM [1] package for the banana that maintains the link between diverse elements of an agro-ecosystem e.g. emphasis on the dynamics of pest-defenders, the natural capacity of plants to repair damage brought on by pests, and the impact of abiotic factors on pest development [1].

C. RI 3: HOW THE DATA HAS BEEN COLLECTED FOR THE PRECISION AGRICULTURE OF BANANAS?

1) AVAILABLE ARCHITECTURES, DATASETS, AND TOOLS

There exist different well-known designs that researchers may use to begin assembling their systems instead of beginning from scratch. These incorporate AlexNet [35], VGG, CaffeNet [36], GoogleNet [37], and Inception-ResNet [6], among others. Every design has various points of interest that make it suitable to be used. It is worth noting that the maximum aforementioned systems come along with the pre-trained weights, which implies that the system had been prepared by some dataset and learned to give exact classification for some specific problem domain [38]. In the study, some technical insights regarding datasets, and software used, were included, but a detailed discussion on the content can be seen

TABLE 3. Variety-wise average yield of banana (tones/ha.).

Variety of banana	Characteristics	Image	Average yield (tones/ha.)	Reference
Grand Naine	Tall heightened plant with a long tube-shaped bunch produces a bundle gauging 25 kilograms, has eight to ten arms with an average of 200 fruits per arm, fruit size is 15-21 cm and circumference is around 12 cm		65	[39]
Robusta	Average height with dark brown patches on the shaft, clumps weighing around 20 kilograms have an average of 8 arms per bundle, size is around 12 cm with a thick peel.		50 – 60	-
Dwarf Cavendish	Tree height is small, berry brown patches are present over the whole stem, bundles are huge with closely organized 8-10 arms having a weight of nearly 20 kilograms, fruit size is around 13 cm, deepness is around 8-10 cm, thick peel, and fruit size continuously decreases towards the tip.		50 - 60	[40]
Red Banana	Towering plant, color is lavender- red, clumps weight is about 20-25 kg, having 6-7 arms and 80 products per pack, and fruit length is about 16-18 cm.		45	-
Nendran	Clumps with 5-6 hands weighting 6-12 kg, fruits stay starchy even on maturing		30- 35	-

in [21]. Fig. 7 presents the open-source based datasets and proprietary data sources.

It has been observed that 19 studies used open-source datasets that included Godliver and Scotnelson (2), COCO dataset (1), and PlantVillage dataset (16). Contrarily, 41 studies have used proprietary datasets collected by different organizations or individuals from different parts of the world. Table 5 shows a comparison of a few DL approaches with their numerous performance metrics which have been used to carry out the analysis of fruit ripeness prediction or disease classification.

2) RI 3.1: WHAT PROGRAMMING INTERFACES HAVE BEEN USED FOR IMPLEMENTATION?

There exist different platforms and tools allowing researchers to practice with DL. The most famous ones are Tensor Flow,

Theano, Keras, Caffe, Pylearn2, TFLearn, and the DL Matlab Toolkit. However, as indicated by our primary picked-up studies, MATLAB, PYTHON, and WEKA are some popular PI’s used for implementation. Table 6 depicts some programming interfaces that are used in our selected primary studies.

D. RI 4: WHAT KIND OF IMAGES HAS BEEN CAPTURED FOR ANALYSIS (RGB, HYPERSPECTRAL)?

A massive number of automatic practices put forward so far depend on digital images, that permit the use of very swift techniques. Most of the procedures explained in the literature are rooted around digital images of manifestation either in visible or near-infrared bands [14]; these bands are reviewed in isolated or regarded in multi imaging and HSI. Even though multi and hyperspectral images can probably convey additional details than ordinary snapshots, these types of images

TABLE 4. Diseases characteristics.

Disease Name	Disease Symptoms	Disease-causing elements	Reference
Panama Wilt	Yellowness starts from the lowermost leaves and starts from the margin; extends in the upward direction.	Fungus	[41]
Mycosphaerella leaf spot, yellow Sigatoka, black Sigatoka	Onset symptoms start from young leaves; Axle-shaped patches on foliage and finally, greenery turns into yellowness; Banana growth remains undersized and pinkish flesh	Fungus	[41]–[48]
Anthrachnose	Initially black, tiny spots appear on the fruit, ultimately patches enlargement occurs; Black rotten banana	Air-borne conidia	[45]
Moko disease/bacterial wilt	Foliage turns yellow and extends upwards; Rotten interior part; Flowing bacteria can be seen easily	Bacteria	[41], [42], [46], [48]
Tip-over or bacterial soft rot	Rotten fruit, emission of foul smell.	Bacteria	[45]
Bunchy top/curly top	Eminent dark green strips on the petioles; Reduced leaves size, turning brittle	Virus	[42], [46]
Banana bract mosaic virus (BBMV)	Drop-shaped pink or red strips are present on the midrib, pseudo stem, and peduncle	Virus	[41], [45]
Banana streak disease (BSV)	Yellow strips on foliage progressively turn black strips in older foliage	Virus	[49], [50]

TABLE 5. Comparison of a few DL approaches with their numerous performance metrics.

DL Architectures	Datasets	Plant	Performance Metrics with their Results	Reference
LeNet	PlantVillage	Banana	CA (98.61%), F1 (98.64%)	[51]
AlexNet, VGG, GoogLeNet, ALexNetOWTBn, Overfeat,	In-field images & PlantVillage	Gourd, apple, onion, eggplant, blueberry, cassava, grape, banana , cabbage, orange, cherry, cucumber, corn, celery, cantaloupe	Performance of VGG is best (99.53%)	[9]
AlexNet, VGG-16	PlantVillage & CASC-IFW	Apple, banana	CA (98.6%)	[10]
Resnet-50, MobileNet-V1, Inception-V2	Real environment	Banana	Mean Average Accuracy (99%) of ResNet-50	[52]
Mask-R CNN	COCO dataset	Banana	CA (96.5%)	[53]

are commonly apprehended by costly and heavy sensors, while traditional cameras are ever-presented. More details on multi and HSI imaging concerned with plant pathology can

be seen in [14] and [60]. Some of the techniques traversing visible range images point to discovering only one ailment of interest amongst other ailments [61]. During the review,

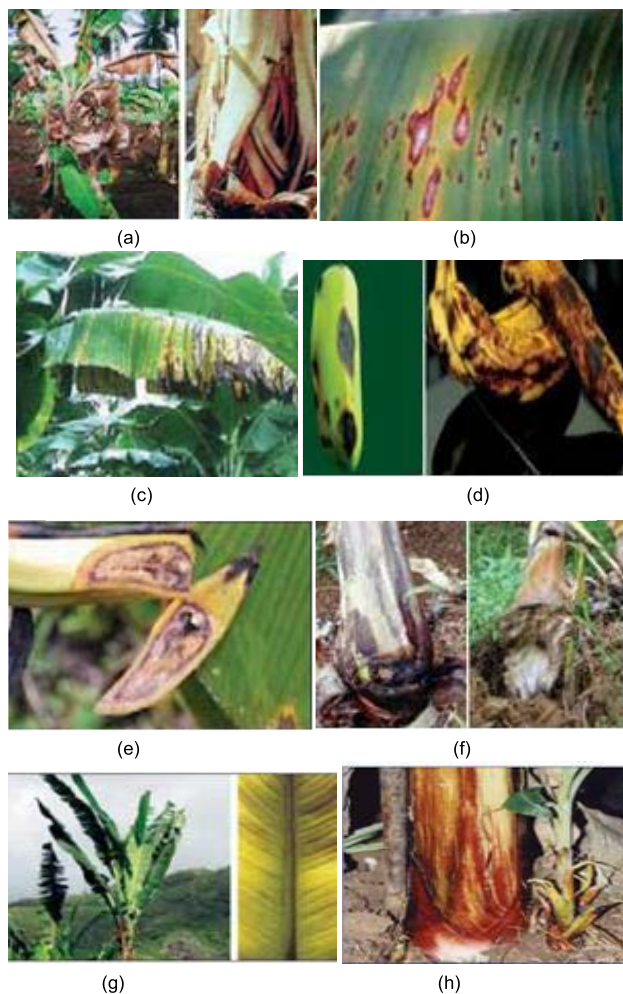


FIGURE 6. This figure shows diseases present on the different parts of the banana plant: (a) Infected plant and stems with Panama Wilt; (b) Yellow Sigatoka; (c) Black Sigatoka; (d) Anthracnose; (e) Moko disease/bacterial wilt; (f) Tip-over or bacterial soft rot; (g) Infected plant and stem with Bunchy top/curly top; (h) Banana bract mosaic virus (BBMV).

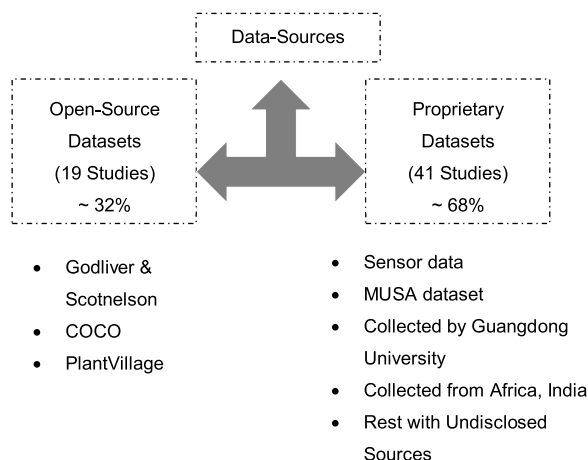


FIGURE 7. Data sources observed from the reviewed studies.

the authors have identified six research papers on HSI and the rest on classic imaging as displayed in Fig. 8. In order to detect diseases in plants, there exist multiple types of image

TABLE 6. Programming tools used in selected primary studies.

Programming Used	Interface/Software	Studies
MATLAB		[4], [5], [7], [37], [42], [43], [45], [46], [50], [54]–[56]
PYTHON		[49], [57]
Colabeler		[57]
WEKA		[58], [59]
Torch7 ML Computational Framework (LuaJIT Programming Language)		[9]
AgiSoft PhotoScan, (Agisoft LLC, St Petersburg, Russia) software		[44]

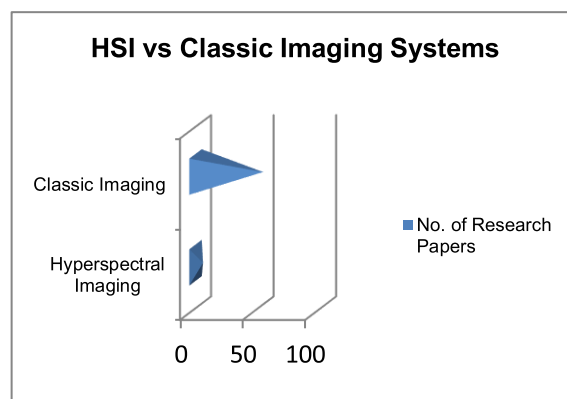


FIGURE 8. Comparison of imaging systems.

acquisition techniques such as thermal imaging, multispectral imaging, fluorescence, and HSI. In these multiple types; HSI is the current research trend. A joint bilateral filter and KNN Classifier were used to detect disease in the banana plant using HSI [8]; gave overall accuracy of 96.87% and average accuracy of 95.06%. Fig. 9 shows some examples of the HSI of the banana fruit. In Fig. 9 (a) browning ratio was used to predict the shelf-life of the banana [55]. Fig. 9 (b) shows the original captured HSI image and 9 (c) represents the enhanced HSI imaging in order to find the sugar content in a banana for a non-destructive measurement system [62].

The modified CARS Method was used to find the optimal wavelength selection in predicting the quality of the banana fruit (predicting the total soluble solid content in banana [72].

The author used HSI on fifteen pieces of banana fruit. Morphological fusion is comprised of using HSI to improve the detection of leaf elements [92]. In [65], an HSI system is used to identify diseases in the banana plant. The shelf life of bananas was predicted using Principal component analysis (PCA), Threshold algorithm, and Backpropagation (BP) with a hyperspectral camera. Shelf-life was predicted with different browning levels on the banana. Multiple linear regressions (MLR), PCA, and Partial least square regression (PLSR) analysis were done for two hundred and seventy fruits

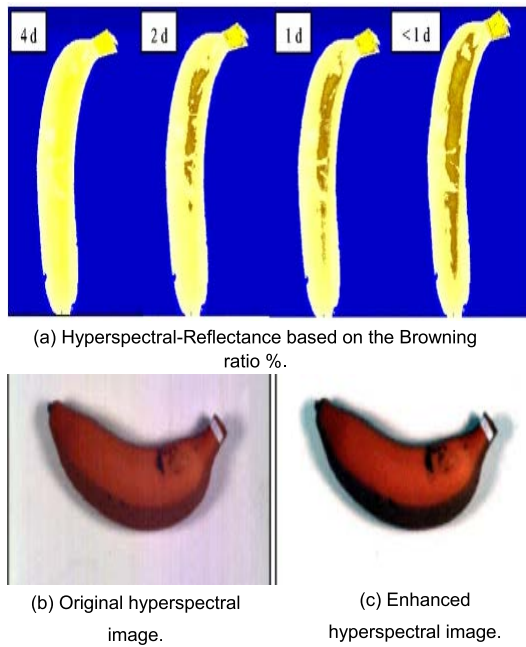


FIGURE 9. Visualization maps to predict the shelf - life of banana using HSI.

using HSI to predict moisture content, firmness, and total soluble solids.

The coefficient of determination was found to be 0.85, 0.87, and 0.91 for the total soluble solids, moisture, and firmness of the banana fruits, respectively [32]. In the review, almost all researchers used their own dataset set in which they captured images using different types of cameras and then labeled the data. Table 7 gives an overview of what type of devices have been used and the resolution of images they have been acquired to carry out the fruit ripeness prediction or disease classification.

E. RI 5: WHICH TECHNIQUES HAVE BEEN USED FOR BANANA DISEASE DETECTION AND FOR OTHER RELATED PROBLEMS? TO SPECIFY THE PREVAILING ML PROCEDURES AND MEASURED FEATURES USED FOR THE ANALYSIS OF BANANA

In Tables 8-16, the authors have mentioned the sixty identified related works, the particular issue they address is about indicating the banana disease identification, fruit grading, ripeness level indication, shelf-life of banana fruit, and some of them are expert systems for disease identification description. The review is also giving details about the techniques implemented, sources of data owned, data pre-processing, and overall performance acquired according to the metrics used, as well as the distinction made with other techniques, wherever applicable.

Overall sixty papers have been investigated as per the area of use, with the eminent ones being banana fruit or leaf diseases detection (17 papers), fruits grading and quality indices (14 papers), crop recommendation system (2 papers) banana

TABLE 7. Image acquisition.

Camera Used	Imaging Technique	Resolution	Reference
CCD camera JVC KY-F50E	RGB	720×576-pixel size	[64]
Charged coupled device (CCD) camera (PCO – 1600, Pco. Imaging) Germany	Hyperspectral	400×400 pixels	[65]
Monocular colored camera, Canon sx610hs	RGB	2048×1536 pixels	[57]
A CCD camera (JVC KY-F50E)	Backscattering images	720×576 pixels	[66]
Olympus SP- 510 UZ.	RGB	3072×2304	[67]
Canon digital camera (model: EOS 550D)	RGB	2,592 ×1728 pixels	[68]
Charged coupled device (CCD) camera (DL-604M, Andor, Chicago, Ireland)	Hyperspectral	-	[55]
Canon EOS 20-D camera	RGB	-	[6]
A high-resolution 12-bit	Hyperspectral	198 × 186 pixels	[69]
Canon EOS 750D Camera	RGB	128×128 pixels	[43]
A UAV equipped with 16-megapixel camera (GSD of 0.016781 m pixel ⁻¹)	RGB	(4000 x 4000 pixels)	[44]

defects classification (2 papers), shelf life and ripeness level detection (15 papers), diagnosis and treatment (1 paper) moisture level indication (3 papers), and nutrient Deficiency (2 papers), and chilling injuries (4 papers) as depicted in Fig. 10.

1) DISEASE DETECTION

In [42], the virtues of both the Gabor filter and the 2D log Gabor filter have been combined in this study to create an upgraded Gabor filter that retrieves characteristics from diseased plant images. Furthermore, the KNN classifier is utilized to classify the present diseases. In comparison to SIFT and SURF feature descriptors, the suggested technique performs better for diseased datasets. In [43], the study illustrates a new ML approach using discoloration patterns on the leaf blade for the categorization of three common foliar fungal diseases: Deightoneilla, Sigatoka, and Cordana. The images were changed to the frequency domain using the discrete orthonormal Stockwell transform after pre-processing

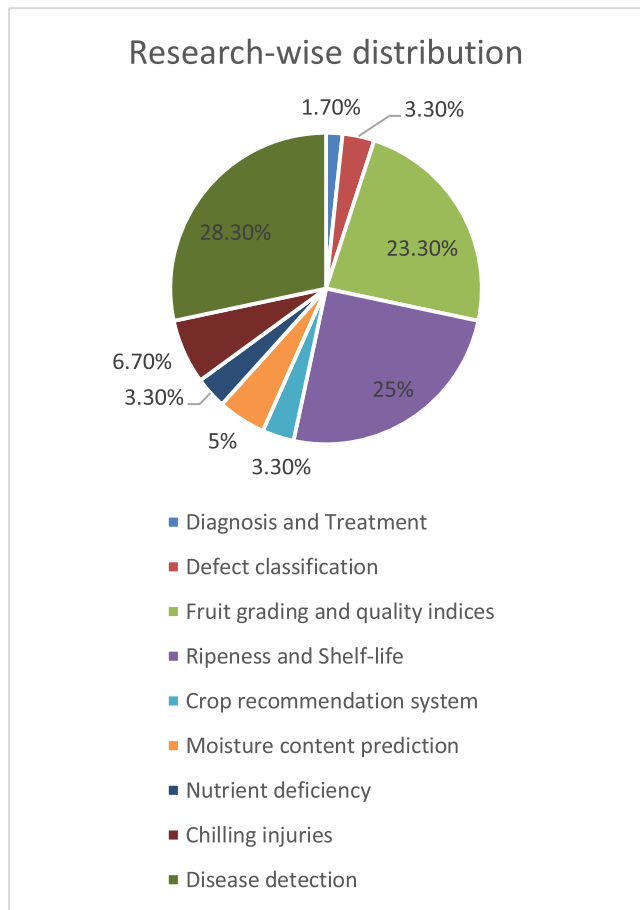


FIGURE 10. Division as per the area of research on the banana.

along with segmentation. Feature vectors were based on local neighborhood patterns such as local binary pattern (LBP), elliptic LBP (ELBP) and classified using five well-known image classifiers. A ten-fold cross validation process was used to compare performance measures. While using an ANN classifier, ELBP characteristics have a CA of 95.9%..

As compared to the existing methods of disease classification in plants, the methodology of merging DOST with LBP-based features has obtained significant accuracy. In [44], the authors’ goal was to employ high spatial resolution aerial photographs to track the amount of a yellow Sigatoka infestation in a banana crop, based on the basic hypotheses of phenotypic factor detection, classification, and prediction. It has been observed that SVM performed best with 99.28% accuracy followed by ANN and other minimum distance-based algorithmic techniques. In [41], the authors explained how to use an automation system to extract color, texture, and shape information to recognize banana plant diseases. Data was classified using SVM classification techniques. The presented work demonstrated an average accuracy of 85% in identifying four diseases: Sigatoka, Bacterial Wilt, CMV, and Panama.

In a similar study [47], texture-based pattern strategies for identifying and classifying diseases in banana plants are discussed. The suggested methodology comprises two

main phases: (a) texture feature extraction using LBP; and (b) categorization of diseased and healthy banana plants. LBP extracts texture information from an improved input image. For the final banana plant disease classification, the collected characteristics are fed into SVM and KNN algorithms. The suggested technique was used to classify two separate experimental scenarios: Healthy-Black Sigatoka, and Healthy-Cordana leaf spot using the Plant Village dataset. Using the SVM classifier, the proposed methodology achieved an accuracy of 89.1%, and 90.9% for two experimental examples. In [46], a new DL technique called Heap Auto Encoders (HAEs) is proposed in this study that could directly extract relevant features while reducing the need for handcrafted features. In addition, the training method’s overfitting difficulty was also lowered, and effectiveness for a small training set was enhanced. HAE additionally employs the dropout approach and the Rectified Linear Units (ReLU) activation function. The proposed technique’s results show that it is superior to traditional procedures. For real data sets, this framework achieves the greatest classification accuracy (CA) of 99.35 %.

Furthermore, in [52], authors have developed a DCNN-based banana diseases and pest recognition system in order to assist field farmers. In another study [8], the authors have combined a close-range HSI image with a high-resolution visible RGB image in order to potentially identify the disease in banana leaves. The joint bilateral filter was used in the technique for transferring the textural structures of the high-resolution RGB image to the low-resolution HSI image. In [9], [10], [51], and [70], authors have deployed several Deep CNNs such as AlexNet, VGG16 and 19, ResNet, InceptionNet, etc. in order to classify various plant diseases. PlantVillage was utilized as the image dataset and transfer learning was used to achieve excellent classification results. Table 8 presents a literature survey of deployed techniques for banana disease classification and detection. It was observed from studies [10], [41], [44], [47], [54], [71] that SVM is the most prominent approach used for disease detection in banana crops with an accuracy range of 80-99.61%. SVM was utilized in 7 studies out of 17 employed for disease detection. Furthermore, it is evident from the studies [8], [42], [47], [54] that KNN is another common approach employed for banana disease detection with an accuracy range of 80-90%. However, CNNs [9], [10], [51], [63] outperformed all other conventional ML algorithms with a successful classification rate of ~ 98-99%.

2) FRUIT GRADING AND QUALITY INDICES

In [57], the authors have used a monocular camera for extracting the deep feature characteristics of banana fruits using the YOLOv4 neural network, resulting in the reliable detection of varied banana sizes. The detection method had a detection rate of 99.29% with an execution time of 0.171 seconds. The dataset was collected from the Guangdong Academy of Agricultural Sciences. The YOLOv3 technique and the ML algorithm were also used to discuss the detection findings.

TABLE 8. Deployment of ML/DL-based techniques for disease detection in banana fruit or plant leaves.

Reference	ML-based Analytical Approach	Extracted Features	Images as Input	Color space	Accuracy/Result
[42]	Gabor filter, K-NN	SIFT, SURF texture features	Scotnelson, Godliver dataset	YCbCr	97% for Scotnelson, 98% Godliver dataset
[43]	Discrete orthonormal Stockwell transform, local binary pattern, ANN	Texture features	900 real-field leaf samples	RGB	95.9%
[44]	SVM	Thematic maps	30 samples	RGB	99.61%
[45]	Adaptive Neuro-Fuzzy Inference System	Color, shape, and texture feature	1000 images	RGB	CA, 96.7%-97.2% For different diseases
[41]	SVM	Color, shape, and texture features	618 images	L*a*b*	85%
[46]	Heap Auto Encoders (HAEs)	Visual features	Godliver, Scotnelson, Plant village, and real-field dataset	YCbCr	CA 99.35%
[47]	Local binary pattern (LBP), SVM, K-NN	Texture features	123 samples from the PlantVillage dataset	LBP	89.1% (Healthy-Black Sigatoka) and 90.9% (Healthy-Cordana leaf spot)
[9]	CNN	Size, texture	5167 images	RGB	Success rate (99.53%)
[10]	Correlation Coefficient and Deep Features (CCDF) M-SVM	Color, texture	6309 images	RGB, YCbCr, HSV	CA (98.6 %)
[51]	Stochastic Gradient Descent Algorithm	Color, shape, and texture	3700 images from the Plant village project	RGB and grayscale	CA (98.61%), F1 (98.64%)
[8]	Joint bilateral filter, KNN Classifier	Morphological features, spectral indices	520 images	Hyperspectral and RGB	Average accuracy 95.06%
[52]	DCNN	-	Diseased banana dataset collected from Africa and India	RGB	~90 %
[54]	MDC with K mean MDC with proposed algorithm SVM with proposed algorithm	Texture and color	15 Images	RGB	80% 90% 90%
[49]	Economic Threshold Level (ETL)	Color of leaf	Image of the plantain tree	HSV	88 % accurate for unaffected, 81.6% accurate for moderately affected, and 84.8 % accurate for fully-affected leaves
[71]	Adaptive Contrast Map method, SVM	Color, texture, and, shape	90 images	RGB, YCbCr, grayscale	-

TABLE 8. (Continued.) Deployment of ML/DL-based techniques for disease detection in banana fruit or plant leaves.

[63]	Motorized stage, optical spectrograph, high-sensitivity VIS-NIR camera	Shape, size, color	520 images	Hyperspectral	-
[48]	Extremely Randomized Trees	Shape	623 Image samples	RGB to HSV, RGB to L*a*b*	BBW disease 96%, BBS 91% and healthy classes 99%

The DL algorithm outperformed the ML approach in terms of detection accuracy and detection time. YOLOv4 exhibited a greater detection rate and confidence in detection than YOLOv3. The purpose of the study is to perform fruit detection in complex background. In [72], authors have used HSI to find the optimal wavelength selection in predicting the quality of the banana fruit. The goal is to find the optimal wavelength selection in predicting the quality of the banana fruit (predicting the total soluble solid content in bananas). In [53], The created model distinguishes normal from aberrant tiers using a real dataset based on banana tiers. DL model achieved a greater average accuracy of 92.5 % than the previous general ML study, which discriminates reject classes from normal classes with a classification CA of 79 %. With only a single image feature instead of the time-consuming multiple image and size characteristics, the prior average weighted accuracy of 94.2 % improved to 96.1 %. With the addition of data, the model improved marginally to 93.8 percent in classifying rejects and 96.5% in total accuracy. This DL classification, which has been successfully deployed in banana tiers, can also be used to classify other clustered horticultural crops.

In [35], extra class, class I, class II, and reject class fruits were categorized and assessed using three popular ML classifiers: ANN, SVM, and random forest. The random forest classifier seemed to have a recognition rate of 94.2%. In [73], with Wavelet, Tamura, and Gabor transforms, the application of a backscattering image acquisition with several methodologies of transform-dependent image texture analysis to evaluate the banana quality at various ripening stages was examined. In [74], the context-based optimal pattern was proposed and recommended to farmers for the following season in order to produce high-quality bananas with the most efficient resources. As per the model, the user will be notified of the disease and pest attack caused by the Sigatoka disease with an accuracy of 74%. Table 9 presents a literature review of techniques deployed for fruit grading and measuring the quality indices of bananas. It has been seen that [73], [75], and [76] performed well with the SVM technique for fruit grading and quality assessment in banana fruit. However, YOLO V4 and Mask R-CNN are the best performers with a 99.29% fruit detection rate in complex backgrounds and 96.5% classification rate for fruits respectively.

3) CROP RECOMMENDATION SYSTEM

In [77], authors have proposed a recommendation system using an ensemble technique with majority voting

approaches deploying CHAID, Random tree, Naive Bayes, and K-Nearest Neighbor as learner algorithms for recommending a crop for the site specifically tuned parameters with good accuracy and high efficiency. Table 10 shows the crop recommendation system deployed in agriculture based on ML techniques.

4) BANANA SHAPE DEFECT DETECTION

In [78], the study provided an image processing algorithm for detecting and calculating defect regions on banana leaves. Processing images, segmentation, labeling, size filtering, and establishing the boundaries for candidate areas e.g. chalks, spider webs, pus banana, soils, and ripped leaves are all part of the algorithm. Color features were extracted to identify faults and, ultimately, to estimate regions. As banana faults cause a lot of leaks, we consider the number of defects to determine if a leaf is good or bad. Experiments were carried out on 200 leaves. The proposed method has an accuracy of 89.8% with color detection of disability defects and 94.7 % for identifying ripped leaves. In [58], the authors have presented a scale-invariant shape analysis with respect to banana cultivar detection. During the experimentation, the chi-square test was identified as the best feature selection algorithm with an optimal feature count of 100. Table 11 presents a review of studies that deployed ML techniques to identify the defects in banana. It has been observed that only a few of the studies employed for the classification of the shape defects present in fruits.

5) SHELF-LIFE AND RIPENESS LEVEL DETECTION

In [84], 4 distinct banana ripeness stages were categorized utilizing the proposed CNN architecture and also compared with the other existing CNN models employing transfer learning. To achieve better classification results using the CNN model, a large count of training images was required. Both original and augmented imagery were used to train and evaluate the suggested CNN model. The model gave a validation accuracy of 96.14%. In [59], the author has developed an expert system platform for determining the maturity of bananas. The program uses the Google Cloud Platform to provide a sample of a banana image using the Google Cloud Vision Application Programming Interface in order to obtain attribute measurements from the image. To assess the ripeness of the banana sample image, the results of the analysis are matched to the application's database of descriptive datasets.

TABLE 9. Deployment of ML/DL-based techniques for fruit grading and quality measurement in bananas.

Reference	ML-based Analytical Approach	Extracted Features	Images as Input	Color space	Accuracy/Result	Purpose
[57]	YOLOv4	Size features	388 samples	RGB	99.29% detection rate	Fruit detection in complex background
[53]	Mask R-CNN	Color and shape features	COCO dataset	Fixed image size	96.5%	Classification of fruits
[35]	Random forest classifier	Red, green, and blue color values, and size dimension	1164 instances	RGB, L*a*b (LAB) color space	94.2%	Fruit classification of banana
[73]	ANN using wavelet features, SVM using wavelet features	Texture analysis	Samples of 270	Laser Light Backscattering Imaging (LLBI) with laser diodes emitting light at three wavelengths viz 532, 660, and 830 nm	SSC with R2 =0.947 followed by elasticity (R2 = 0.927) and the chlorophyll index (R2 = 0.810) R2 is equal to 0.927, 0.878, and 0.918 for elasticity, SSC, and the chlorophyll index respectively.	Evaluation of banana quality
[75]	BPNN RBFN SVM	Texture based	200 Images	RGB to Grayscale	98.8 % 96.25 % 100 %	Grading of Banana
[58]	Scale-Invariant Shape Analysis using Bayesian Network	Color, shape, and texture	231 Samples	YCbCr color system	84 %	Banana Cultivar Classification
[74]	Context-based optimal pattern	Size and color	Sensor	-	74%	To produce quality banana
[72]	Modified CARS Method	Color, soluble solid content, firmness, and moisture content	15 pieces of banana	Hyperspectral image	Square of the relative error of 0.09 and the correlation coefficient R2 of 0.97	Predicting the total soluble solid content in banana
[76]	Support Vector Regression ANN	Color features	25 Samples	RGB, L*a*b* and HSV	92 % 91.65 %	Prediction of Banana quality indices
[79]	BPNN	Texture	600 bananas	RGB, Grayscale	98%	Grading of Banana
[68]	Two-step k-Means	Damage lesions and senescent	Four banana fingers	RGB	R ² 0.9991	Senescent spots, mechanical injuries,

TABLE 9. (Continued.) Deployment of ML/DL-based techniques for fruit grading and quality measurement in bananas.

	Clustering technique	spots on the banana surface				residual tissues, and shadows were adequately segmented
[67]	Mean Color Intensity Algorithm	Color and size value	120 images	RGB	99.1%	Classification of the under-mature fruit
	Area Algorithm				85 %	
[80]	Hunter Color Lab and Texture Analyzer	Textural attributes of bananas	Nine bananas	Color ('L', 'a' and 'b' value)	Pulp firmness, peel toughness, and pulp toughness showed R ² above 0.84	Prediction of textural attributes
[81]	BP neural network	Surface color of the fruit	10 Banana images	RGB	-	Fruit quality measurement

TABLE 10. Deployment of ML/DL-based techniques for crop recommendation systems.

Reference	ML-based Analytical Approach	Extracted Features	Images as Input	Accuracy/ Result	Purpose
[77]	Ensembling technique (K- Nearest Neighbor, Random Tree, Naive Bayes, CHAID)	Texture, PH, Soil Color	Data set collected from Tamil Nadu	88 %	Prediction of crops
[82]	Multivariate Cross-Classification (MVCC)	Cross-Modal Sensory Representations	-	-	Fruit image classification

TABLE 11. Deployment of ML/DL-based techniques for identifying defects in banana fruit.

Reference	ML-based Analytical Approach	Extracted Features	Images as Input	Color space	Accuracy/ Result	Purpose
[78]	Image segmentation algorithm	Color	200 banana leaves	HSV	Color identification of disability defects 89.8% and identifying torn leaves 94.7%	Detection and Classification Defects on Exported Banana Leaves
[69]	Morphological fusion	Shapes and size	520 images	Hyperspectral images	Consumes less time	To improve the detection of leaf elements
[83]	BP neural network classifier	Size and shape	600 images	RGB to Grayscale conversion	Recognition rate 97%	To identify whether a banana is defective or healthy
[50]	FCM algorithm for background elimination and ANN	Boundaries of a sample banana	Sample of five hundred bananas	Gray level	-	Detection of healthy bananas and defective

In [85], hyperspectral images were used to describe 300 banana samples that were either naturally ripened or ripened with the artificial agent (ethephon or calcium

carbide). Different preprocessing procedures were examined to increase the performance of classification models and to eliminate the impact of noise and irregular surfaces. The

successive projections algorithm (SPA) and recursive feature elimination (RFE) were used to pick feature wavelengths. For ripening detection, four classification algorithms were used: XGBoost, SVM, MLP, and PLS-DA. XGBoost based on complete wavelengths was found to be the best classification model. In [5], the authors used a fuzzy logic technique to construct an automated system for determining the shelf-life of a Cavendish banana fruit based on its ethylene gas level. The ethylene gas released by the fruit is measured using an MQ3 sensor, while the temperature range inside the chamber is monitored using a DHT22 temperature sensor. The modified R Square result was 0.94, according to linear regression analysis statistics. The system includes MATLAB to calculate the shelf-life of bananas using the fuzzy logic toolbox, which is shown in a graphical user interface. In a similar research [4], a fuzzy controller was used with RGB images in order to determine the banana quality and then segregate these using a low-cost method.

Furthermore, in [86], the authors have proposed the development of a device that could determine if a banana has been artificially or organically ripened. It has a motor, a banana holder for rotating the fruit, an image processing part, a camera, and a display unit. The device is made up of a banana holder mechanism, a motor to rotate it, and an embedded camera to acquire the surface image of the fruit. Images captured are fed into an image processing unit. To determine whether the fruit has been artificially matured or not, the image is processed and matched to a reference image. In [87], the authors have proposed a design that was assessed using the MUSA database, which contains banana samples at various stages of ripening. Experimental results reveal that the fuzzy model outperforms state-of-the-art algorithms with an average classification rate of 93.11 %. In [6], the authors have deployed the k-means algorithm to extract the colored features of bananas and then detect the different ripeness stages of it. In [56], the authors have used an Arduino to detect the distinct ripeness stages, [37] deployed the GSM modem to extract the color indices from bananas and monitor the ripeness stages with an accuracy of 93%, and [36] used SVM deployed for the shelf-life monitoring. Table 12 deploys various ML-based techniques in order to predict the ripeness and shelf-life of banana fruit. It is evident that SVM is a common performer in the classification of ripeness stages and prediction of the shelf-life of bananas using studies [36], [88], [89] with a rate of 96-99%. Meanwhile, CNN and XGBoost are the two best performers with a ripeness classification rate of up to 100%.

6) DIAGNOSIS AND TREATMENT

In [45], the Adaptive Neuro-Fuzzy Inference System and case-based reasoning techniques were employed for classification purposes. The decision is then made using fuzzy logic. The Receiver Operating Characteristics (ROC) curve was used to analyze the proposed system. According to the findings, the Adaptive Neuro-Fuzzy Inference System outperforms the case-based reasoning system. It gave a

CA of banana leaf spot disease diagnosis (97.1%), banana anthracnose disease (96.7%), banana cigar-end tip rot disease (97.1%), banana crown rot disease (96.9%), and banana virus disease (97.2%) In [90], CLIPS was used to create the expert system, with Delphi 10.2 as the user interface. In studying instances of evaluated banana disease, the expert system produced good results, allowing the system to make the proper diagnosis in all cases. Table 13 provides the details of the studies used for the diagnosis and treatment of the banana.

7) MOISTURE LEVEL INDICATION

In [92], the Visual-NIR imaging approach was used to establish a banana moisture content prediction system. Reflectance image profile measurement, spatial data, and feature extraction on spectral, and moisture prediction models are all part of the system's software. On the full wavelength range of HSI spectra, the feature sets were generated using PCA and PLSR. The goal of the study was to compare the results of moisture content prediction using two regression approaches. A total of 45 Raja bananas were used to test the proposed technique, with 15 samples one per maturity stage. With PCR, the prediction error between predicted and measured data was 0.58 %, resulting in an R^2 correlation coefficient of 0.79. The banana content prediction system's PLSR model has an RMSE of 0.25 %. In another study, [72], a strategy for determining the best wavelength selection for predicting banana fruit quality (*Musa sp.*) was described. The reduction of wavelength dimension was done in two steps. To determine a candidate for the ideal band, the peak and valley detection of reflectance profiles from sample data was performed. Using the Standard deviation information, the modified CARS approach was utilized to determine the optimal wavelength. The predicted value was then computed using the PLS registration and the transfer model established with the training data. To compare the performance of different wavelengths, the squared relative errors and correlation coefficient were chosen. The modified CARS approach provides the best results with a correlation coefficient R^2 of 0.97 for the prediction of the total soluble content in fruit.

In a similar study [65], authors have studied the presence of moisture content and the maturity stage of bananas using PCA, MLR, and optimal wavelengths were deployed in order to predict the quality features. The coefficients of determination for total soluble solids, firmness, and moisture of banana fruits were determined to be 0.85, 0.91, and 0.87 respectively. Table 14 deliberates the summary of ML/DL-based techniques to detect the presence of moisture content in banana fruit.

8) CHILLING INJURIES

In [64], the effect of chilling injury on the color of bananas at various stages of ripening was studied. To eliminate the brightness, the raw RGB values were converted to normalized RGB and CIEL*a*b* space. To analyze the overall color difference of the samples, the total color difference (E)

TABLE 12. Deployment of ML/DL-based techniques for detection and prediction of ripeness and shelf-life in banana fruit.

Reference	ML-based Analytical Approach	Extracted Features	Images as Input	Color space	Accuracy/Result	Purpose
[84]	CNN	Features based on filters	273 Images	RGB	96.14%	Banana ripeness stage identification
[85]	Recursive feature elimination (RFE), successive projections algorithm (SPA), extreme gradient boosting (XGBoost)	Feature wavelength	300 banana samples	Hyperspectral	100%	Classification of naturally ripened and artificially ripened bananas
[5]	Fuzzy logic approach	Ethylene gas content and ambient temperature	1 finger of banana	Sensor	Adjusted R Square 0.94	To determine the progression rate of banana's ripeness and determine the shelf life of banana fruit
[59]	Utilizing Google Cloud Platform and Google Cloud Vision Application Programming Interface	Color dominance	338 sample images	RGB	96.15%	Banana Ripeness Evaluation
[4]	Fuzzy logic controller	Color	Hundred samples of banana	RGB	-	To classify the banana into various categories of ripeness
[86]	Microcontroller with a Stepper motor	Size	-	Cyan, Magenta, Yellow, and Black (CMYK) format	-	Detection of artificial ripening of banana fruit
[87]	Classification and Regression Tree (CART) algorithm, parameters of the fuzzy model are tuned with Particle Swarm Optimization technique (PSO)	Color	MUSA database (3108 images of banana hands)	CIEL a*b*	93.11%	Ripeness Classification
[6]	K- Means Decision Tree Classifier	Color features	46 Bananas	H, S, I, L, a*, b*, % yellow, % brown, % green	52 %	Banana ripeness states Shelf-life
[56]	Arduino serially, GSM	Color of banana	-	RGB	-	Supervision of banana ripening stages
[37]	GSM Modem	color indices	-	RGB	93%	Monitoring of Banana Ripening Process

TABLE 12. (Continued.) Deployment of ML/DL-based techniques for detection and prediction of ripeness and shelf-life in banana fruit.

[36]	SVM	Peel colors	30 Samples	Color value L*, a*, and b*	96.5 %	Classification of ripening stages
[88]	BackPropagation Multilayer Perceptron (BP-MLP) Neural Network, SVM	Aroma	2 Bananas	Sensor arrays	Ripening 97.33% Senescence 94.44%	Banana classification (Shelf-life Process)
[55]	PCA, Threshold algorithm, BP	The shape of reflectance curves of banana, color	200 samples	Hyperspectral images	Classification rates of 95.6% for the training set and 90.5% for the testing set, respectively	To predict the shelf life of bananas with different browning levels
[89]	SVM	Aroma fingerprint	15 Bananas as Sample	Sensor array	98.66 %	Ripeness Monitoring
[91]	2-D spectral analysis	Surface color spots	Ten immature bananas	Two broad-spectral images under white light and ultraviolet illuminations	-	Ripeness Level Indication

TABLE 13. Deployment of ML/DL-based techniques for diagnosis and treatment in banana fruit or plant leaves.

Reference	ML-based Analytical Approach	Extracted Features	Images as Input	Color space	Accuracy/ Result	Purpose
[90]	Knowledge-based CLIPS with Delphi 10.2 as UI	-	-	-	-	Diagnosis and Treatment

was determined using the CIEL*a*b* space. To grade the severity of the injury and correlate it with color characteristics, a visual examination was performed. The color changes due to variations in the fruit chlorophyll concentration were assessed using visible wavelength spectroscopy in diffuse reflectance geometry. Temperature, ripening stage, and post-chilling time all had a substantial (P 0.0001) impact on color characteristics, according to the findings. The r, g, and H color parameters were shown to have strong relationships ($R^2 > 0.9$) with visual assessment.

In [7], the variation in backscattering characteristics in bananas during the onset of chilling injury was examined. A camera was used to capture the backscattered lights that flashed on the samples after laser beams with wavelengths of 660 nm and 785 nm were blasted successively onto the samples in a dark environment. The collected images were analyzed, and graphs depicting variations in intensity as a function of pixel count were created. Backscattering parameters such as inflection point (IP), full width at half maximum (FWHM), slope after inflection point (SA), and

TABLE 14. Deployment of ML/DL-based techniques for moisture level indication in banana fruit or plant leaves.

Reference	ML-based Analytical Approach	Extracted Features	Images as Input	Color space	Accuracy/ Result
[92]	PCA and PLSR	Shape	45 Raja bananas (Musa textilla) samples	HSI spectra	Prediction Value of Reflectance (Predicted Value) based on maturity level has an error of 0.25% and a correlation coefficient value (R2) of 0.96
[65]	MLR, PCA, PLSR	Moisture content, firmness, and total soluble solids	Two hundred and seventy fruits	HSI	Coefficient of determination: total soluble solids- 0.85, moisture-0.87, and firmness- 0.91.

TABLE 15. Deployment of ML/DL-based techniques in order to recognize the chilling injuries.

Reference	ML-based Analytical Approach	Extracted Features	Images as Input	Color space	Accuracy/ Result	Purpose
[7]	Backscattering imaging method and visual assessment	Back-scattering parameters	Six images	Back-scattering	Laser-induced backscattering imaging using 660 and 785 nm wavelength lights has shown to be a good method	To investigate the change in backscattering parameters during the appearance of chilling injury in bananas
[66]	Multi-linear regression analysis	Changes in visual assessment, water content, and pigments contents	60 fruits	Back-scattering image	Classification of control and chill-injured samples in ripe fruits measured at 660 nm and 785 nm resulted in misclassification errors as low as 6% and 8% for early detection, and 0.67% and 1.33% for detection after storage, respectively	Monitoring the chilling injury appearance in bananas, to monitor chlorophyll and texture changes utilizing relevant wavelengths, respectively
[64]	PCA	Degree of injury and Color parameters	Thirty-nine fingers of bananas	RGB, HIS, CIEL*a*b*	Variances in the range of 79.83%- 91.57%	Kinetic Model for Colour Changes in Bananas During the Appearance of Chilling Injury Symptoms

saturation radius were all represented on the graph (RSAT). The results of statistical research revealed that these backscattering parameters changed significantly as the chilling injury progressed. Table 15 summarizes the techniques deployed in the literature in order to recognize the chilling injuries caused during the storage of fruit.

9) NUTRIENT DEFICIENCY

In [93], the authors have developed LeafCheckIT, a web and mobile application that employs a Random Forest ML algorithm to detect nitrogen (N), potassium (K), and phosphorus (P) nutrients shortage symptoms on banana leaves. The technique employed in the application achieved 100 and 91.64 % accuracy rates, respectively, depending on the training dataset

and 10-fold cross-validation test done on WEKA data mining software. In a similar study [94], textural properties in form of the linear expansion ratio, porosity, crispness, color, and bulk density were studied as the nutrient measurement criteria in banana fruit. Table 16 presents a summary of deployed techniques in order to recognize the macro-nutrient in banana fruit.

F. RI 6: WHAT KIND OF PERFORMANCE METRICS ARE USED TO MEASURE THE EXTRACTED FEATURES IN OUR STUDIES?

Performance metrics have a lion’s share in the evaluation of ML algorithms. In the review, the authors have analyzed the performance-measuring criterion for the banana disease

TABLE 16. Deployment of ML/DL-based techniques to identify the nutrient deficiency in fruit.

Reference	ML-based Analytical Approach	Extracted Features	Images as Input	Color space	Accuracy/ Result
[93]	SVM	Color and texture features	705 leaf images consisting of healthy, nitrogen, phosphorus, and potassium leaf deficiency and non-leaf images	RGB, YCbCr, and CIELab	Training set evaluation 93.61% 10 fold Validation test 87.53%
	ANN				Training set evaluation 99.29% 10 fold Validation test 87.67%
	Naïve Bayes				Training set evaluation 86.64% 10 fold Validation test 85.83%
	Random Forest Algorithm				Training set evaluation 100% 10-fold Validation test 91.64s%
[94]	Green banana flour (GBF), as a functional ingredient	Linear expansion ratio, crispness, bulk density, porosity, and color	Fifteen samples	-	Influence of green banana flour substitution for cassava starch on the nutrition, color, texture, and sensory quality in two types of snacks

classification, moisture measurement, chilly injuries measurement, and ripeness measurement. Table 17 shows that there have been multiple metrics used for assessment like F-score, R², RMSE, CA, etc.

G. RI 7: HOW HAVE BEEN DL MODELS IMPLEMENTED WITH OR WITHOUT VISUALIZATION TECHNIQUES?

1) IMPLEMENTATION OF DL MODELS USING VISUALIZATION TECHNIQUES

Data visualization is a crucial step to build an efficient and powerful machine-learning model. It makes us understand data in a better way and produces a better understanding of feature engineering; and at last, performs better results during training and modeling of the learning model. Image filtering, histograms, scatter plots, etc. are ways of visualization. While implementing the DL models, a clearer comprehension of plant disease is given using visualization techniques. In paper [52], a leaf disease detection for the banana plant was performed with the help of CNN Models (MobileNet-V1, Inception-V2 and ResNet-50) with SSD detectors and faster CNN. The author proposed a contemporary visualization technique in [10] by using correlation coefficients and DL models like VGG-16 and AlexNet architectures. In [64], a visual assessment is performed for grading chilling injuries in bananas and correlating with color parameters. The coefficient of determination (R²) was found to be very strong between color parameters and visual assessment. According to visual assessment, bananas chilled at a controlled temperature are not degraded by chilling injuries. Spectral reflectance of banana was used as performance visualization [65].

Hyperspectral data analysis, optimal wavelength selection, and multiple regression models were used to evaluate the banana fruit quality and their maturity stages. Even if

TABLE 17. Performance metrics used in the review.

Performance Metrics used	Studies under review
R ² (Coefficient of Determination)	[64]–[66], [73], [75], [92]
SSE (Sum of Squares of Errors)	[64], [65]
RMSE (Root Mean Squares of Errors)	[64], [66]
MEAN, Standard Deviation	[7], [73], [75]
Chi-Square, Information Gain, Gain Ratio	[58]
SSC (Soluble Sugar Content)	[4]
CA (Classification Accuracy)	[41], [45]–[47], [53], [83]–[85], [87]
Precision	[45], [53], [57], [84], [87]
Recall	[57], [84], [87]
F- Score	[46], [53], [57], [84], [87]
ROC	[44], [45]
Success Rate, Average error	[9]
RMSEC (RMSE for Calibration)	[73]
Sensitivity, Precision, Specificity, Accuracy, FPR (false positive rate)	[10], [42], [45], [47]
RMSECV (RMSE for Cross Validation)	[73]
Classification Error	[87]

visualization is an easy way of evaluation, chilling injuries were used to be very difficult to estimate at the starting phase of storage, which leads to misclassification errors [66].

TABLE 18. Summary of visualization techniques.

Visualization Techniques used	Selected Papers
Visualization maps using browning ratio, combined image features, average spectra	[55]
Impedance, Color difference	[4]
Image segmentation	[54]
Clustered image segmentation	[43]
Peak hue, normalized brown area (NBA)	[87]
Region of interest, peak valley detection, reflectance profile, wavelength selection	[72]
Change of reference parameters, backscattering profiles	[73]
Thematic maps	[44]
L*a*b color space, contrast, Gray cluster index, Adaptive Histogram Equalization Contrast enhancement technique	[41]
Filtering of images, edge detection using Sobel Operator, image true color to grayscale	[79]
Changes in textural properties	[80]
Filtering of images	[75]
Edge detection, Morphological operation, Filtering, Thresholding	[83]
Color Histograms	[81]
Kinetic of color change, the correlation between color parameters	[64]
Saliency map, mesh graph, 2D and 3D contour	[10]
Expectation-Maximization	[46]
LBP Histograms	[47]

In [7], images were acquired using backscattering, and immediately after then, the visual assessment is carried out using a browning scale. Scale readings are in the range from 0-5 which goes from no chilling injuries to very severe injuries respectively. There are a lot of visualization mappings that have been reviewed in the study, a detailed summary of used visualizations is shown in Table 18.

2) IMPLEMENTATION OF DL MODELS WITHOUT USING VISUALIZATION TECHNIQUES

To find out the diseases in banana leaves, the LeNet framework was applied over training data, and F1- score and CA were owned for evaluating the system in Grayscale and color modes [51]. Overfeat, AlexNet, GoogLeNet, AlexNetOWTbn, and VGG architectures are five CNN that were used in the study [9], where the VGG framework performed best among all models.

H. RI 8: HOW IS THE INDIVIDUAL PREDICTION MODEL USED TO EVALUATE THE ML ALGORITHM AND WHAT IS THE BEST-FITTED MODEL (WHEREVER APPLICABLE)?

The authors have explored many individual prediction models that have been used in our selected primary studies of

bananas (disease detection, ripeness indication, and chilling injuries) and found the best-performing model from each paper. Table 19 presents a brief of the investigations that have utilized individual models and the best-fitted ones (wherever applicable) to anticipate the studies on bananas. The choice of the best-fitted model depends on the estimation measures that evaluate and compare the prediction efficiency of prediction models used in each study. On the behalf of these estimation measures, the best-fitted ones are recommended in each of the research papers.

I. RI9: HOW DO EXTRINSIC AND INTRINSIC FACTORS AFFECT THE IDENTIFICATION PROCESS?

Laboratory investigations are tedious. In specific circumstances, it is convincing to develop programmable techniques capable of identifying plant diseases in a reliable furthermore, fast way. In any case, extrinsic and intrinsic factors mean these strategies remain too error-prone. A description of these factors is depicted in Table 20.

V. DISCUSSIONS

The study found that most of the studies have made direct, logical, and correct comparisons between the ML-based state-of-the-art techniques utilized to solve the specific problem addressed in each paper. Since each publication used distinct image samples, preprocessing approaches, metrics, modeling techniques, and parameters; thus generalization is quite complex. As a result, the authors have limited the comparisons to the approaches employed in each publication. As a consequence of the applied constraints, the authors have shown that ML excels with the usage of conventional methods like SVM, RF, ANN, KNN classifiers, and others. It appears that the results are more promising with the ML techniques when utilized in combination with the potent feature extraction methods such as GLCM, SIFT, histograms, statistics-based, texture-based, color-based, and shape-based algorithms, as well as other mechanical feature extraction methods. It was observed from studies ([10], [41], [44], [47], [54], [71]) that SVM is the most prominent approach used for the disease detection in banana crops with an accuracy range of 80-99.61%. SVM was utilized in 7 studies out of 17 employed for disease detection. Subsequently, [73], [75], and [76] performed well with the SVM technique for fruit grading and quality assessment in banana fruit. Moreover, the authors have remarked on its performance in the classification of ripeness stages and prediction of the shelf-life of bananas using studies [36], [88], [89]. In [93], Random Forest and SVM were used to monitor the nutrient deficiency in fruit using color and texture features. Furthermore, it is evident from the studies [8], [42], [47], [54] that KNN is another common approach employed for banana disease detection with an accuracy range of 80-90%.

It has been observed that most of the ML and DL techniques have been applied to image analysis and computer vision of banana fruit and leaves in order to detect the present diseases. Authors have also discovered some more fields of

TABLE 19. Individual prediction model with best-fitted prediction model used in the review.

Research Paper ID	Result	Prediction models used	Best-fitted prediction model
[73]	Chlorophyll index, $R^2 = 0.908$, Elasticity, $R^2 = 0.901$, SSC, $R^2 = 0.910$	ANN using wavelet features	Wavelet features with ANN
	Chlorophyll index, $R^2 = 0.694$, SSC, $R^2 = 0.899$, Elasticity, $R^2 = 0.848$	SVM using wavelet features	
	Chlorophyll index, $R^2 = 0.767$, SSC, $R^2 = 0.887$, Elasticity, $R^2 = 0.819$	ANN using Gabor Transform	
	Chlorophyll index, $R^2 = 0.738$, SSC, $R^2 = 0.852$, Elasticity, $R^2 = 0.587$	SVM using Gabor Transform	
	Chlorophyll index, $R^2 = 0.869$, SSC, $R^2 = 0.931$, Elasticity, $R^2 = 0.920$	ANN using Tamura Transform	
	Chlorophyll index, $R^2 = 0.805$, SSC, $R^2 = 0.887$, Elasticity, $R^2 = 0.697$	SVM using Tamura Transform	
[75]	R^2 , 98.8 %	BPNN	SVM
	R^2 , 96.25 %	RBFN	
	R^2 , 100 %	SVM	
[93]	Training set evaluation 93.61%	SVM	Random Forest
	10-fold Validation test 87.53%		Algorithm
	Training set evaluation 99.29%	ANN	
	10-fold Validation test 87.67%		
	Training set evaluation 86.64%	Naïve Bayes	
	10-fold Validation test 85.83%		
	Training set evaluation 100%	Random Forest Algorithm	
	10-fold Validation test 91.64s%		
[54]	CA, 80%	MDC + K mean	MDC with proposed
	CA, 90%	MDC + proposed algorithm	algorithm and SVM with
	CA, 90%	SVM + proposed algorithm	proposed algorithm
			performs equally
[76]	R^2 , 92%	Support Vector Regression	Support Vector
	R^2 , 91.65%	ANN	Regression
[67]	CA, 99.1%	Mean Color Intensity Algorithm	Mean Color Intensity
	CA, 85%	Area Algorithm	Algorithm

agricultural-related activities for banana crops e.g. detecting the moisture presence ([65], [92]), monitoring of ripeness stages of bananas, detection of nutritional deficiency ([93], [94]), chilling injuries detection ([7], [64], [66]), etc. Most of the work has been carried out for disease detection and ripeness monitoring as well as to monitor the shelf-life of fruit. There is a need to focus on the rest aspects also as addressed above. These studies are significant contributions to the DL community since they aim to overcome the problem related to crop production in a variety of applications. Although many of the studies employed pure ML techniques for the classification task (36 papers). Moreover, 16 papers were discovered that employ a hybridization of ML and DL techniques. Subsequently, it has been seen that only 8 studies out of the total ones were utilized with DL techniques.

VI. CHALLENGES AND FUTURE SCOPE

Banana is an adaptable fleshy product that might be major nourishment and can be consumed as crude or can be prepared. The most significant quality attributes of agricultural commodities are size, texture, shape, color, and deformity. To supplant manual examination of nourishment, a computer vision framework is utilized which gives a credible, fair and non-damaging rating. Quality investigation of fruits contains four primary steps, 1) acquisition, 2) segmentation, 3) feature extraction, and 4) classification. In the review, an endeavor has been made to do the investigation and made a comparison of several techniques/algorithms recommended by the authors. Although many researchers have suggested different strategies for the quality investigation of fruits; still a robust framework with improved results is required to be

TABLE 20. Extrinsic & intrinsic factors.

Factors	Sub-factors	Description	Reference
Extrinsic factors	Image background	Leaf area division or segmentation is the initial step of image-based techniques for leaf analysis. In the state where some sort of board (ideally white or blue) is set behind the leaf, then the assignment can normally be carried out automatically without much issue. On the other part, if the background area is busy with plants, leaves, or any other things, then it is very challenging to perform segmentation.	[95]
	Image capture conditions	Several elements may influence the attributes of the images, making it progressively inflexible for an automatic algorithm to play out a significant analysis. Preferably, all images ought to be caught under similar conditions. Practically speaking, this must be accomplished in a controlled domain, for example, a lab. Luminescence concerns are particularly significant in the field, where viewpoints, for example, time of day, the position of the sun regarding the leaf, and cloudy conditions, can incredibly influence image qualities.	[60]
Intrinsic factors	Symptom segmentation	Most manifestations do not have well-characterized edges. Rather, they continuously blur into solid tissue. As a result, the unambiguous segmentation is not there. If manual, visual depiction cannot distinctly decide the boundary, then any machine-based outline opens to the intuitive question as well.	[96]
	Symptom variations	A typical assumption related to explicit disease identification proof is that the manifestations will consistently have similar characteristics. For sure, numerous disease indications are characterized and promptly distinguished by an expert. There may be perpetually some variety in the shading, shape, and size of manifestations. This makes issues for image-based diagnostics utilizing the visible range of spectrum to depict 'healthy' or 'sick' pixels. A few ailments produce indications that are exceptionally heterogeneous and that have a profound factor dispersion, making them hard to describe.	[34]
	Multiple simultaneous disorders	Many algorithms expect that just a single disease exists in each image. However, different diseases or other types of disorders like nutritional deficiencies and pests may apparently show at the same time.	[97]
	Different disorders with similar symptoms	One of the fundamental difficulties looked by strategies for automated plant disease diagnosis is the likeness of the indications among various disorders, which incorporate diseases, pests, nutritional deficiencies, and differed mechanical harm. The scope of potential disorders is wide, making it extremely challenging to distinguish the birthplaces of a given manifestation with assurance, particularly if just the noticeable range of the spectrum is utilized.	[98]

constructed. Here a few challenges are addressed that are also kept in mind while implementing a robust framework:

–While capturing the images of fruits or leaves, only one direction is considered, but more angles need to cover up

during the image acquisition, e.g. diseases may also be present on the lower side of the leaf or on the hanging tip of the fruit. Moreover, stem and root could also get the infections and spread the disease to the other parts of the plant, and

sometimes it became too late to perform the diagnosis of the diseased part. Hence, this could be another challenge in the direction.

—In most of the studies, the PlantVillage dataset is utilized as a source of data to estimate the performance and accuracy of the corresponding DL model. Moreover, it contains a large number of images of different plants with the diseases present either in the leaves or fruit of the plant. All the images are with a simple background but for practical applications, real habitat is needed to be considered.

—Another considerable challenge is the requirement of huge datasets that could act as input in the course of the training period. For example, the authors in [99] and [100] remarked that a diversified training dataset was expected to produce a better CA.

—A major issue with numerous datasets is the moderate variety among the various classes [101], or the presence of noise, such as low resolutions, imprecision of sensory equipment [102], yields' occlusions, foliage overlapping, and grouping, and many more.

As researchers claimed data annotation is an important activity in the vast lion's share of cases, a few tasks are very complicated and there is a requirement for specialists (who may be hard to include) to comment on input images. As referenced in [51] Amara *et al.* [51], there is restricted accessibility of expertise and assets on banana pathology around the world. Sometimes, specialists or volunteers are defenseless to mistakes while labeling the data, particularly for a difficult assignment like counting fruits [103], [104] or to decide whether pictures compromise weeds or not [105]. Another challenge in the way of fruit disease prediction or classification is that the models can get familiar with some particular problems especially well, yet they cannot generalize later than the "limits of the dataset's expressiveness." A genuine application ought to have the option to classify captured images of several diseases as it presents itself straightforwardly on the plant. Numerous diseases do not only present on the upper hand side of leaves as it were.

A common issue in computer vision, not just in DL, many times information preprocessing is tedious and time-taking task, particularly when satellite or airborne photographs are included. Furthermore, HSI is a rising technology and should be deployed with a suitable DL framework in the real environment to find the diseases as soon as their symptoms start to appear clearly but an issue with hyperspectral information is their high dimensionality and restricted training data samples [106]. Also, many a time the present datasets do not depict the issue they target [102]. Finally, for the area of farming, there do not exist numerous openly accessible datasets for analysts to work with, and much of the time, researchers need to build up their arrangements of images. This could require numerous hours or long stretches of work.

Other conceivable application territories could be the utilization of aerial imagery (i.e. by using drones) to monitor the adequacy of the seeding procedure, to improve the quality of banana production by reaping crops at the correct minute

for best development levels, to monitor the movements of animals and distinguish potential diseases, and numerous different situations where computer vision is included. Later on, exploiting the time measurement (dimension) to perform higher-order performance prediction or classification is also an issue. A model application could be to evaluate the development of plants, trees, or even creatures' dependent on past back-to-back perceptions, to anticipate their yield, survey their water needs, or keep away from infectious diseases from occurring. Specialists are required to test their models utilizing progressively broad and practical datasets, exhibiting the capacity of the models, to sum up, different real-world circumstances. It would be attractive if scientists made their datasets openly accessible, for use additionally by the general research network. At long last, a portion of the solutions talked about in the overviewed papers could have an industrial use sooner. The methodologies fusing Faster Region-based CNN and DetectNet CNN [103], [104], [107] would be amazingly helpful for programmed robots that gather crops, evacuate weeds, or for evaluating the normal yields of different harvests. Future utilization of this system could be likewise in microbiology for human or creature cell checking [104].

To accomplish more and more exactness in the prediction, different forms of neural networks were utilized. In the review, the authors have recognized the extreme utilization of neural networks, and seven such investigations were found. Regression was utilized multiple times whereas the fuzzy model was utilized in just two investigations. There is a certain restriction in existing work like more accuracy and optimization is needed, priori data is required for segmentation, database expansion is required to arrive at more precision, only a few diseases have been identified or there have been multiple diseases could be present at the same time. Thus, work should be done to reach out to cover more ailments. The potential reasons that can prompt misclassification can be the following: manifestation varies from plant to plant, features optimization is required, and more training data samples are required to wrap more instances and to foresee the disease more precisely. The previously mentioned findings can be utilized in building up a grading framework for the banana agro-industry based on the quick prediction of quality attributes of the natural product. The researchers are additionally advised to investigate the utilization of evolutionary algorithm techniques and join them with different fields, for example, genetic algorithms, nature-inspired algorithms, data mining, artificial intelligence, expert systems, and so on.

VII. CONCLUSION

In the systematic review, the authors have carried out a study of problems related to banana crops such as disease classification, chilling injuries detection, ripeness, maturity level-based defects identification, presence of moisture content, etc. based research endeavors applied in the farming domain using ML techniques. The authors have recognized sixty relevant research papers that deployed ML

techniques, inspecting the specific area of deployment and issue they center on, adopted data sources, pre-processing assignments, and techniques used for data augmentation and final performance obtained by using performance metrics deployed in each study. It has been observed that sixteen papers have used the plantVillage dataset, five papers used acquired images from real-field conditions, two studies used Godliver and Scotnelson datasets, one study used the COCO dataset, and the rest have reported the experimental results with anonymous or limited private datasets. The authors have then compared the applied ML approaches and other existing systems, concerning their performance wherever applicable.

The motive of the systematic literature review is to propel more researchers to analyze around there, applying it for tackling different farming issues including prediction or classification, identified with computer vision and image analysis. The general advantages of this review are empowering for its further use towards more intuitive, progressively sustainable cultivation, and increasingly secure banana production. The precision still should have been required to implement practical applications to the marketing of this fruit. The authors have also discussed the current key challenges and trends in employing ML techniques and advanced imaging technologies to recognize the above-mentioned problems relevant to the banana crop. The authors have anticipated that this study will be useful to researchers who are interested in the investigation of defects and diseases related to banana plants or any other crop. At the same time, the authors remarked on a few of the challenges and issues that need to be addressed in the domain. As expected in the future, the authors intend to apply the general ideas and best implementations of banana disease classification and grading of banana fruits, as portrayed through the overview, to different regions of agribusiness where this innovative procedure has not yet been properly utilized.

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REFERENCES

- [1] K. Satyagopal, “AESA based IPM package for banana,” Dept. Agricult. Cooperation, Ministry Agricult., Government India, Nat. Inst. Plant Health Manage., Hyderabad, India, Tech. Rep., 2014, p. 46.
- [2] T. Ball, L. Vrydaghs, I. Van Den Hauwe, J. Manwaring, and E. D. Langhe, “Differentiating banana phytoliths: Wild and edible *musa acuminata* and *musa balbisiana*,” *J. Archaeolog. Sci.*, vol. 33, no. 9, pp. 1228–1236, Sep. 2006.
- [3] K. A. Ajjolakewu, A. S. Ayoola, T. O. Agbabiaka, F. R. Zakariyah, N. R. Ahmed, O. J. Oyedele, and A. Sani, “A review of the ethnomedicinal, antimicrobial, and phytochemical properties of *Musa paradisiaca* (plantain),” *Bull. Nat. Res. Centre*, vol. 45, no. 1, pp. 1–17, Dec. 2021.
- [4] M. N. Kulkarni and R. P. Mudhalwadkar, “Data driven modelling for banana ripeness assessment,” in *Proc. Int. Conf. Intell. Comput. Control Syst. (ICICCS)*, Jun. 2017, pp. 662–665.
- [5] D. M. Taghoy and J. F. Villaverde, “A fuzzy logic approach for the determination of cavendish banana shelf life,” in *Proc. TENCON IEEE Region Conf.*, Oct. 2018, pp. 2467–2472.
- [6] N. Thor, “Applying machine learning clustering and classification to predict banana ripeness states and shelf life,” *Int. J. Food Sci. Technol.*, vol. 2, no. 1, pp. 20–25, 2017.
- [7] N. Hashim, R. B. Janius, R. A. Rahman, A. Osman, M. Shitan, and M. Zude, “Changes of backscattering parameters during chilling injury in bananas,” *J. Eng. Sci. Technol.*, vol. 9, no. 3, pp. 314–325, 2014.
- [8] W. Liao, D. Ochoa, Y. Zhao, G. M. V. Rugel, and W. Philips, “Banana disease detection by fusion of close range hyperspectral image and high-resolution RGB image,” in *Proc. IEEE Int. Geosci. Remote Sens. Symp.*, Jul. 2018, pp. 1744–1747, doi: 10.1109/IGARSS.2018.8519115.
- [9] K. P. Ferentinos, “Deep learning models for plant disease detection and diagnosis,” *Comput. Electron. Agricult.*, vol. 145, pp. 311–318, Feb. 2018.
- [10] M. A. Khan, “CCDF: Automatic system for segmentation and recognition of fruit crops diseases based on correlation coefficient and deep CNN features,” *Comput. Electron. Agricult.*, vol. 155, pp. 220–236, Dec. 2018.
- [11] A. Kamilaris, A. Kartakoullis, and F. X. Prenafeta-Boldú, “A review on the practice of big data analysis in agriculture,” *Comput. Electron. Agricult.*, vol. 143, no. 1, pp. 23–37, 2017.
- [12] A. Kamilaris, F. Gao, F. X. Prenafeta-Boldu, and M. I. Ali, “Agri-IoT: A semantic framework for Internet of Things-enabled smart farming applications,” in *Proc. IEEE 3rd World Forum Internet Things (WF-IoT)*, Dec. 2016, pp. 442–447.
- [13] W. G. Bastiaanssen, D. J. Molden, and I. W. Makin, “Remote sensing for irrigated agriculture: Examples from research and possible applications,” *Agric. Water Manage.*, vol. 46, no. 2, pp. 137–155, 2000.
- [14] J. G. A. Barbedo, “Digital image processing techniques for detecting, quantifying and classifying plant diseases,” *SpringerPlus*, vol. 2, no. 1, p. 660, Dec. 2013.
- [15] G. ElMasry and D.-W. Sun, “Principles of hyperspectral imaging technology,” in *Hyperspectral Imaging for Food Quality Analysis and Control*. Amsterdam, The Netherlands: Elsevier, 2010, pp. 3–43.
- [16] B. Lu, P. Dao, J. Liu, Y. He, and J. Shang, “Recent advances of hyperspectral imaging technology and applications in agriculture,” *Remote Sens.*, vol. 12, no. 16, p. 2659, Aug. 2020.
- [17] A. Khan, A. D. Vibhute, S. Mali, and C. H. Patil, “A systematic review on hyperspectral imaging technology with a machine and deep learning methodology for agricultural applications,” *Ecolog. Informat.*, vol. 69, Jul. 2022, Art. no. 101678.
- [18] X. Chu, P. Miao, K. Zhang, H. Wei, H. Fu, H. Liu, H. Jiang, and Z. Ma, “Green banana maturity classification and quality evaluation using hyperspectral imaging,” *Agriculture*, vol. 12, no. 4, p. 530, Apr. 2022.
- [19] M. I. A. Abenina, J. M. Maja, M. Cutulle, J. C. Melgar, and H. Liu, “Prediction of potassium in peach leaves using hyperspectral imaging and multivariate analysis,” *AgriEngineering*, vol. 4, no. 2, pp. 400–413, Apr. 2022.
- [20] K. R. Ball, H. Liu, C. Brien, B. Berger, S. A. Power, and E. Pendall, “Hyperspectral imaging predicts yield and nitrogen content in grass-legume polycultures,” *Precis. Agricult.*, vol. 1, pp. 1–19, Jul. 2022.
- [21] A. Kamilaris and F. X. Boldú, “Deep learning in agriculture: A survey,” *Comput. Electron. Agricult.*, vol. 147, pp. 70–90, Apr. 2018.
- [22] R. A. Mouha and others, “Deep learning for robotics,” *J. Data Anal. Inf. Process.*, vol. 9, no. 2, p. 63, 2021.
- [23] N. Sünderhauf, O. Brock, W. Scheirer, R. Hadsell, D. Fox, J. Leitner, B. Upcroft, P. Abbeel, W. Burgard, M. Milford, and P. Corke, “The limits and potentials of deep learning for robotics,” *Int. J. Robot. Res.*, vol. 37, nos. 4–5, pp. 405–420, 2018.
- [24] C. Luo, L. Yu, J. Yan, Z. Li, P. Ren, X. Bai, E. Yang, and Y. Liu, “Autonomous detection of damage to multiple steel surfaces from 360° panoramas using deep neural networks,” *Comput.-Aided Civil Infrastruct. Eng.*, vol. 36, no. 12, pp. 1585–1599, Dec. 2021.
- [25] F. Zeng, X. Cai, and S. S. Ge, “Low-shot wall defect detection for autonomous decoration robots using deep reinforcement learning,” *J. Robot.*, vol. 2020, pp. 1–7, Sep. 2020.
- [26] W.-J. Chang, Y.-X. Yu, J.-H. Chen, Z.-Y. Zhang, S.-J. Ko, T.-H. Yang, C.-H. Hsu, L.-B. Chen, and M.-C. Chen, “A deep learning based wearable medicines recognition system for visually impaired people,” in *Proc. IEEE Int. Conf. Artif. Intell. Circuits Syst. (AICAS)*, Mar. 2019, pp. 207–208.
- [27] S. M. Usman, S. Khalid, and M. H. Aslam, “Epileptic seizures prediction using deep learning techniques,” *IEEE Access*, vol. 8, pp. 39998–40007, 2020.
- [28] B. Kitchenham, *Procedures for Performing Systematic Reviews*, vol. 33. Keele, U.K.: Keele Univ., 2004, pp. 1–26.

- [29] R. C. Ploetz, "Panama disease: A classic and destructive disease of banana," *Plant Health Prog.*, vol. 1, no. 1, p. 10, Jan. 2000.
- [30] D. H. Marín, R. A. Romero, M. Guzmán, and T. B. Sutton, "Black Sigatoka: An increasing threat to banana cultivation," *Plant Disease*, vol. 87, no. 3, pp. 208–222, Mar. 2003.
- [31] J. D. Pujari, R. Yakkundimath, and A. S. Byadgi, "Grading and classification of anthracnose fungal disease of fruits based on statistical texture features," *Int. J. Adv. Sci. Technol.*, vol. 52, no. 1, pp. 121–132, 2013.
- [32] Q. Liu, Y. Yuan, J. Liang, C. Wei, Q. Zhang, and H. Li, "Physiological and biochemical characteristics and multilocus sequence analysis of banana soft rot bacteria in China," *J. Plant Pathol.*, vol. 97, no. 1, pp. 69–75, 2015.
- [33] E. K. Allam, J. L. Dale, S. I. El-Afifi, R. M. Harding, and A. S. Sadik, "Chemiluminescent and colorimetric techniques for the detection of banana bunchy top virus," *Pakistan J. Biotechnol.*, vol. 5, nos. 1–2, pp. 101–107, 2008.
- [34] A. Camargo and J. S. Smith, "An image-processing based algorithm to automatically identify plant disease visual symptoms," *Biosyst. Eng.*, vol. 102, no. 1, pp. 9–21, 2009.
- [35] E. J. Piedad, J. I. Larada, G. J. Pojas, and L. V. V. Ferrer, "Postharvest classification of banana (*Musa acuminata*) using tier-based machine learning," *Postharvest Biol. Technol.*, vol. 145, pp. 93–100, Nov. 2018.
- [36] H. Juncai, H. Yaohua, H. Lixia, G. Kangquan, and T. Satake, "Classification of ripening stages of bananas based on support vector machine," *Int. J. Agric. Biol. Eng.*, vol. 8, no. 6, pp. 99–103, 2015.
- [37] A. Verma, R. Hegadi, and K. Sahu, "Development of an effective system for remote monitoring of banana ripening process," in *Proc. IEEE Int. WIE Conf. Electr. Comput. Eng. (WIECON-ECE)*, Dec. 2015, pp. 534–537.
- [38] S. Pan and Q. Yang, "A survey on transfer learning," *IEEE Trans. Knowl. Data Eng.*, vol. 22, pp. 1345–1359, Nov. 2010.
- [39] L. A. Calvo-Valverde, M. Guzmán-Quesada, and J. A. Guzmán-Álvarez, "Considerations about application of machine learning to the prediction of Sigatoka disease," *CIGR Proc.*, vol. 1, no. 1, pp. 1–8, Jul. 2014.
- [40] C. Y. Liew and C. Y. Lau, "Determination of quality parameters in Cavendish banana during ripening by NIR spectroscopy," *Int. Food Res. J.*, vol. 19, pp. 751–758, 2012.
- [41] V. Chaudhari and M. Patil, "Banana leaf disease detection using K-means clustering and feature extraction techniques," in *Proc. Int. Conf. Adv. Comput., Commun. Mater. (ICACCM)*, Aug. 2020, pp. 126–130.
- [42] N. A. B. Mary, A. R. Singh, and S. Athisayamani, "Classification of banana leaf diseases using enhanced Gabor feature descriptor," in *Inventive Communication and Computational Technologies*. Cham, Switzerland: Springer, 2021, pp. 229–242.
- [43] D. Mathew, C. S. Kumar, and K. A. Cherian, "Application of discrete orthonormal stockwell transform and local neighborhood patterns for leaf disease classification in banana," in *Proc. Int. Conf. Commun., Control Inf. Sci. (ICCIsc)*, Jun. 2021, pp. 1–5.
- [44] V. B. C. Calou, A. D. S. Teixeira, L. C. J. Moreira, C. S. Lima, J. B. de Oliveira, and M. R. R. de Oliveira, "The use of UAVs in monitoring yellow sigatoka in banana," *Biosystems Eng.*, vol. 193, pp. 115–125, May 2020.
- [45] A. Athiraja and P. Vijayakumar, "Banana disease diagnosis using computer vision and machine learning methods," *J. Ambient Intell. Humaniz. Comput.*, vol. 12, no. 6, pp. 6537–6556, 2021.
- [46] N. A. B. Mary, A. R. Singh, and S. Athisayamani, "Banana leaf diseased image classification using novel HEAP auto encoder (HAE) deep learning," *Multimedia Tools Appl.*, vol. 79, nos. 41–42, pp. 30601–30613, Nov. 2020.
- [47] A. Aruraj, A. Alex, M. S. P. Subathra, N. J. Sairamya, S. T. George, and S. E. V. Edwards, "Detection and classification of diseases of banana plant using local binary pattern and support vector machine," in *Proc. 2nd Int. Conf. Signal Process. Commun. (ICSPC)*, Mar. 2019, pp. 231–235.
- [48] G. Owomugisha, J. A. Quinn, E. Mwebaze, and J. Lwasa, "Automated vision-based diagnosis of banana bacterial wilt disease and black Sigatoka disease," in *Proc. Int. Conf. Mobile ICT*, vol. 1, Dec. 2014, pp. 1–5.
- [49] K. G. and P. N., "Detection and prevention of banana leaf diseases from banana plant using embedded Linux board," in *Proc. Online Int. Conf. Green Eng. Technol. (IC-GET)*, Nov. 2016, pp. 1–5.
- [50] M. S. Mans, H. Fardad, R. Enteshari, and Y. S. Mansouri, "Isolating healthy bananas from unhealthy ones based on feature extraction and clustering method using neural network," *Modern Appl. Sci.*, vol. 4, no. 11, p. 51, Oct. 2010.
- [51] J. Amara, B. Bouaziz, A. Algergawy, and others, "A deep learning-based approach for banana leaf diseases classification," in *Proc. BTW (Workshops)*, 2017, pp. 79–88.
- [52] M. G. Selvaraj, A. Vergara, H. Ruiz, N. Safari, S. Elayabalan, W. Ocimati, and G. Blomme, "AI-powered banana diseases and pest detection," *Plant Methods*, vol. 15, no. 1, pp. 1–11, Dec. 2019.
- [53] T.-T. Le, C.-Y. Lin, and E. J. Piedad, "Deep learning for non-invasive classification of clustered horticultural crops—A case for banana fruit tiers," *Postharvest Biol. Technol.*, vol. 156, Oct. 2019, Art. no. 110922.
- [54] V. Singh and A. K. Misra, "Detection of plant leaf diseases using image segmentation and soft computing techniques," *Inf. Process. Agricult.*, vol. 4, pp. 41–49, Mar. 2017.
- [55] N.-N. Wang, Y.-C. Yang, D.-W. Sun, H. Pu, and Z. Zhu, "Shelf-life prediction of 'Gros Michel' bananas with different browning levels using hyperspectral reflectance imaging," *Food Anal. Methods*, vol. 8, no. 5, pp. 1173–1184, May 2015.
- [56] B. S. Butola, P. K. Sharma, Y. Singh, and Y. Amin, "Arduino based supervision of banana ripening stages," in *Proc. 1st Int. Conf. Next Gener. Comput. Technol. (NGCT)*, Sep. 2015, pp. 921–924.
- [57] L. Fu, J. Duan, X. Zou, J. Lin, L. Zhao, J. Li, and Z. Yang, "Fast and accurate detection of banana fruits in complex background orchards," *IEEE Access*, vol. 8, pp. 196835–196846, 2020.
- [58] K. Dittakan, N. Theera-Ampornpund, W. Witthayarat, S. Hinnoy, S. Klaiwan, and T. Pratheep, "Banana cultivar classification using scale invariant shape analysis," in *Proc. 2nd Int. Conf. Inf. Technol. (INCIT)*, Nov. 2017, pp. 1–6.
- [59] K. Kipli, H. Zen, M. Sawawi, M. S. M. Noor, N. Julai, N. Junaidi, M. I. S. M. Razali, K. L. Chin, and S. M. W. Masra, "Image processing mobile application for banana ripeness evaluation," in *Proc. Int. Conf. Comput. Approach Smart Syst. Design Appl. (ICASSDA)*, Aug. 2018, pp. 1–5.
- [60] C. H. Bock, G. H. Poole, P. E. Parker, and T. R. Gottwald, "Plant disease severity estimated visually, by digital photography and image analysis, and by hyperspectral imaging," *Crit. Rev. Plant Sci.*, vol. 29, no. 2, pp. 59–107, Mar. 2010.
- [61] J. G. A. Barbedo, C. S. Tibola, and J. M. C. Fernandes, "Detecting fusarium head blight in wheat kernels using hyperspectral imaging," *Biosyst. Eng.*, vol. 131, pp. 65–76, Mar. 2015.
- [62] D. Akmalia, A. H. Saputro, and W. Handayani, "A non-destruction measurement system based on hyperspectral imaging for sugar content in banana (*Musa sp.*)," in *Proc. Int. Seminar Sensors, Instrum., Meas. Metrol. (ISSIMM)*, Aug. 2017, pp. 91–94.
- [63] D. Ochoa, J. Cevallos, G. Vargas, R. Criollo, D. Romero, R. Castro, and O. Bayona, "Hyperspectral imaging system for disease scanning on banana plants," *Proc. SPIE*, vol. 2016, vol. 9864, May 2016, Art. no. 98640M.
- [64] N. Hashim, R. B. Janius, L. Baranyai, R. A. Rahman, A. Osman, and M. Zude, "Kinetic model for colour changes in bananas during the appearance of chilling injury symptoms," *Food Bioprocess Technol.*, vol. 5, no. 8, pp. 2952–2963, Nov. 2012, doi: 10.1007/s11947-011-0646-z.
- [65] P. Rajkumar, N. Wang, G. Elmasry, G. S. V. Raghavan, and Y. Garipey, "Studies on banana fruit quality and maturity stages using hyperspectral imaging," *J. Food Eng.*, vol. 108, no. 1, pp. 194–200, Jan. 2012.
- [66] N. Hashim, M. Pflanz, C. Regen, R. B. Janius, R. A. Rahman, A. Osman, M. Shitan, and M. Zude, "An approach for monitoring the chilling injury appearance in bananas by means of backscattering imaging," *J. Food Eng.*, vol. 116, no. 1, pp. 28–36, May 2013.
- [67] D. S. Prabha and J. S. Kumar, "Assessment of banana fruit maturity by image processing technique," *J. Food Sci. Technol.*, vol. 52, no. 3, pp. 1316–1327, Mar. 2015.
- [68] M.-H. Hu, Q.-L. Dong, B.-L. Liu, and P. K. Malakar, "The potential of double K-means clustering for banana image segmentation," *J. Food Process Eng.*, vol. 37, no. 1, pp. 10–18, Feb. 2014.
- [69] G. Villegas, W. Liao, R. Criollo, W. Philips, and D. Ochoa, "Detection of leaf structures in close-range hyperspectral images using morphological fusion," *Geo-Spatial Inf. Sci.*, vol. 20, no. 4, pp. 325–332, Oct. 2017.
- [70] R. C. Joshi, M. Kaushik, M. K. Dutta, A. Srivastava, and N. Choudhary, "VirLeafNet: Automatic analysis and viral disease diagnosis using deep-learning in vigna mungo plant," *Ecolog. Informat.*, vol. 61, Mar. 2021, Art. no. 101197, doi: 10.1016/j.ecoinf.2020.101197.
- [71] M. J. Vipinadas and A. Thamizharasi, "Banana leaf disease identification technique," *Int. J. Adv. Eng. Res. Sci.*, vol. 3, no. 6, 2016, Art. no. 236756.
- [72] A. H. Saputro and W. Handayani, "Wavelength selection in hyperspectral imaging for prediction banana fruit quality," in *Proc. Int. Conf. Electr. Eng. Informat. (ICELTICs)*, Oct. 2017, pp. 226–230.

- [73] N. Hashim, S. E. Adebayo, K. Abdan, and M. Hanafi, "Comparative study of transform-based image texture analysis for the evaluation of banana quality using an optical backscattering system," *Postharvest Biol. Technol.*, vol. 135, pp. 38–50, Jan. 2018.
- [74] S. Pujari and N. Bogiri, "Precision agriculture for banana using wireless sensor network," in *Proc. Int. Conf. Comput., Commun., Control Autom. (ICCUBE)*, Aug. 2017, pp. 1–6.
- [75] E. O. Olaniyi, A. A. Adekunle, T. Odekuoye, and A. Khashman, "Automatic system for grading banana using GLCM texture feature extraction and neural network arbitrations," *J. Food Process Eng.*, vol. 40, no. 6, Dec. 2017, Art. no. e12575.
- [76] A. Sanaeifar, A. Bakhshipour, and M. de la Guardia, "Prediction of banana quality indices from color features using support vector regression," *Talanta*, vol. 148, pp. 54–61, Feb. 2016.
- [77] S. Pudumalar, E. Ramanujam, R. H. Rajashree, C. Kavya, T. Kiruthika, and J. Nisha, "Crop recommendation system for precision agriculture," in *Proc. 8th Int. Conf. Adv. Comput. (ICoAC)*, Jan. 2017, pp. 32–36, doi: 10.1109/ICoAC.2017.7951740.
- [78] D. T. Dat, N. D. X. Hai, and N. T. Thinh, "Detection and classification defects on exported banana leaves by computer vision," in *Proc. Int. Conf. Syst. Sci. Eng. (ICSSE)*, Jul. 2019, pp. 609–613.
- [79] K. Dimililer and E. O. Olaniyi, "Intelligent sorting system based on computer vision for banana industry," *Int. J. Sci. Eng. Res.*, vol. 6, no. 9, p. 332–337, 2015.
- [80] P. Jaiswal, S. N. Jha, P. P. Kaur, R. Bhardwaj, A. K. Singh, and V. Wadhawan, "Prediction of textural attributes using color values of banana (*Musa sapientum*) during ripening," *J. Food Sci. Technol.*, vol. 51, no. 6, pp. 1179–1184, Jun. 2014, doi: 10.1007/s13197-012-0614-2.
- [81] Y. Wang, Y. Cui, S. Chen, P. Zhang, H. Huang, and G. Q. Huang, "Study on fruit quality measurement and evaluation based on color identification," *Proc. SPIE*, vol. 7513, Nov. 2009, Art. no. 75130F.
- [82] J. T. Kaplan, K. Man, and S. G. Greening, "Multivariate cross-classification: Applying machine learning techniques to characterize abstraction in neural representations," *Frontiers Hum. Neurosci.*, vol. 9, p. 151, Mar. 2015.
- [83] E. O. Olaniyi, O. K. Oyedotun, and K. Adnan, "Intelligent grading system for banana fruit using neural network arbitration," *J. Food Process Eng.*, vol. 40, no. 1, Feb. 2017, Art. no. e12335.
- [84] N. Saranya, K. Srinivasan, and S. K. P. Kumar, "Banana ripeness stage identification: A deep learning approach," *J. Ambient Intell. Humaniz. Comput.*, vol. 13, no. 8, pp. 4033–4039, 2021.
- [85] W. He, H. He, F. Wang, S. Wang, R. Li, J. Chang, and C. Li, "Rapid and uninvative characterization of bananas by hyperspectral imaging with extreme gradient boosting (XGBoost)," *Anal. Lett.*, vol. 55, no. 4, pp. 620–633, 2021, doi: 10.1080/00032719.2021.1952214.
- [86] V. Hallur, B. Atharga, A. Hosur, B. Binjawadagi, and K. Bhat, "Design and development of a portable instrument for the detection of artificial ripening of banana fruit," in *Proc. Int. Conf. Circuits, Commun., Control Comput.*, Nov. 2014, pp. 139–140.
- [87] S. Marimuthu and S. M. M. Roomi, "Particle swarm optimized fuzzy model for the classification of banana ripeness," *IEEE Sensors J.*, vol. 17, no. 15, pp. 4903–4915, Aug. 2017, doi: 10.1109/JSEN.2017.2715222.
- [88] A. Sanaeifar, S. S. Mohtasebi, M. Ghasemi-Varnamkhasti, and M. Siadat, "Application of an electronic nose system coupled with artificial neural network for classification of banana samples during shelf-life process," in *Proc. Int. Conf. Control, Decis. Inf. Technol. (CoDIT)*, Nov. 2014, pp. 753–757.
- [89] A. Sanaeifar, S. S. Mohtasebi, M. Ghasemi-Varnamkhasti, H. Ahmadi, and J. Lozano, "Development and application of a new low cost electronic nose for the ripeness monitoring of banana using computational techniques (PCA, LDA, SIMCA, and SVM)," *Czech J. Food Sci.*, vol. 32, no. 6, pp. 538–548, 2014.
- [90] H. R. Almadhoun and S. S. A. Naser, "Banana knowledge based system diagnosis and treatment," *Int. J. Academic Pedagogical Res.*, vol. 2, pp. 1–11, Aug. 2018.
- [91] Y. Intaravanne, S. Sumriddetchkajorn, and J. Nukeaw, "Ripeness level indication of bananas with visible and fluorescent spectral images," in *Proc. 9th Int. Conf. Electr. Eng./Electron., Comput., Telecommun. Inf. Technol.*, May 2012, pp. 1–4.
- [92] S. T. W. Siregar, W. Handayani, and A. H. Saputro, "Bananas moisture content prediction system using visual-NIR imaging," in *Proc. 5th Int. Conf. Instrum., Control, Autom. (ICA)*, Aug. 2017, pp. 89–92.
- [93] J. A. Tejada and G. P. P. Gara, "LeafcheckIT: A banana leaf analyzer for identifying macronutrient deficiency," in *Proc. 3rd Int. Conf. Commun. Inf. Process. (ICCIP)*, 2017, pp. 458–463.
- [94] Y. Wang, M. Zhang, and A. S. Mujumdar, "Influence of green banana flour substitution for cassava starch on the nutrition, color, texture and sensory quality in two types of snacks," *LWT Food Sci. Technol.*, vol. 47, no. 1, pp. 175–182, Jun. 2012.
- [95] M. Zhang and Q. Meng, "Automatic citrus canker detection from leaf images captured in field," *Pattern Recognit. Lett.*, vol. 32, no. 15, pp. 2036–2046, Nov. 2011.
- [96] C. H. Bock, P. E. Parker, A. Z. Cook, and T. R. Gottwald, "Visual rating and the use of image analysis for assessing different symptoms of citrus canker on grapefruit leaves," *Plant Disease*, vol. 92, no. 4, pp. 530–541, Apr. 2008.
- [97] C. H. Bock, A. Z. Cook, P. E. Parker, and T. R. Gottwald, "Automated image analysis of the severity of foliar citrus canker symptoms," *Plant Disease*, vol. 93, no. 6, pp. 660–665, Jun. 2009.
- [98] J. G. A. Barbedo, "An automatic method to detect and measure leaf disease symptoms using digital image processing," *Plant Disease*, vol. 98, no. 12, pp. 1709–1716, Dec. 2014.
- [99] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," *Frontiers Plant Sci.*, vol. 7, p. 1419, Sep. 2016.
- [100] I. Sa, Z. Ge, F. Dayoub, B. Upcroft, T. Perez, and C. Mccool, "DeepFruits: A fruit detection system using deep neural networks," *Sensors*, vol. 16, no. 8, p. 1222, 2016.
- [101] H. Yalcin, "Plant phenology recognition using deep learning: Deep-phenology," in *Proc. 6th Int. Conf. Agro-Geoinform.*, Aug. 2017, pp. 1–5.
- [102] X. Song, G. Zhang, F. Liu, D. Li, Y. Zhao, and J. Yang, "Modeling spatio-temporal distribution of soil moisture by deep learning-based cellular automata model," *J. Arid Land*, vol. 8, no. 5, pp. 734–748, Oct. 2016.
- [103] S. Bargoti and J. Underwood, "Deep fruit detection in orchards," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, May 2017, pp. 3626–3633.
- [104] S. W. Chen, S. S. Shivakumar, S. Dcunha, J. Das, E. Okon, C. Qu, C. J. Taylor, and V. Kumar, "Counting apples and oranges with deep learning: A data-driven approach," *IEEE Robot. Autom. Lett.*, vol. 2, no. 2, pp. 781–788, Apr. 2017.
- [105] R. A. Sørensen, J. Rasmussen, J. Nielsen, and R. N. Jørgensen, "Thistle detection using convolutional neural networks," in *Proc. EFITA WCCA Congr.*, Jul. 2017, p. 161.
- [106] Y. Chen, Z. Lin, X. Zhao, G. Wang, and Y. Gu, "Deep learning-based classification of hyperspectral data," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 7, no. 6, pp. 2094–2107, Jun. 2014.
- [107] M. Rahmemonfar and C. Sheppard, "Deep count: Fruit counting based on deep simulated learning," *Sensors*, vol. 17, no. 4, p. 905, Apr. 2017.



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