algorithms

MDPI

Review

Machine Learning in Cereal Crops Disease Detection: A Review

Fraol Gelana Waldamichael [1], Taye Girma Debelee [1,2,*], Friedhelm Schwenker [3], Yehualashet Megersa Ayano [1] and Samuel Rahimeto Kebede [1,4]

1 Ethiopian Artificial Intelligence Institute, Addis Ababa 40782, Ethiopia; fraolgela@gmail.com (F.G.W.); yehualeuven@gmail.com (Y.M.A.); samuelrahimeto@gmail.com (S.R.K.)
2 College of Electrical and Mechanical Engineering, Addis Ababa Science and Technology University, Addis Ababa 120611, Ethiopia
3 Institute of Neural Information Processing, Ulm University, 89081 Ulm, Germany; friedhelm.schwenker@uni-ulm.de
4 Department of Electrical and Computer Engineering, Debre Berhan University, Debre Berhan 445, Ethiopia
* Correspondence: tayegirma@gmail.com

Abstract: Cereals are an important and major source of the human diet. They constitute more than two-thirds of the world's food source and cover more than 56% of the world's cultivatable land. These important sources of food are affected by a variety of damaging diseases, causing significant loss in annual production. In this regard, detection of diseases at an early stage and quantification of the severity has acquired the urgent attention of researchers worldwide. One emerging and popular approach for this task is the utilization of machine learning techniques. In this work, we have identified the most common and damaging diseases affecting cereal crop production, and we also reviewed 45 works performed on the detection and classification of various diseases that occur on six cereal crops within the past five years. In addition, we identified and summarised numerous publicly available datasets for each cereal crop, which the lack thereof we identified as the main challenges faced for researching the application of machine learning in cereal crop detection. In this survey, we identified deep convolutional neural networks trained on hyperspectral data as the most effective approach for early detection of diseases and transfer learning as the most commonly used and yielding the best result training method.

Keywords: cereal crop; plant disease; machine learning; deep learning

Citation: Waldamichael, F.G.; Debelee, T.G.; Schwenker, F.; Ayano, Y.M.; Kebede, S.R. Machine Learning in Cereal Crops Disease Detection: A Review. *Algorithms* **2022**, *15*, 75. https://doi.org/10.3390/a15030075

Academic Editor: Frank Werner

Received: 30 January 2022
Accepted: 22 February 2022
Published: 24 February 2022

1. Introduction

Advancements in the area of machine learning and computer vision in the past decade had had a profound effect on the utilization of machine learning techniques in different sectors [1]. Machine learning approaches are being used from the medical [2–9] to the security sector [10]. Recently, many works [11] have been undertaken on the application of machine learning in the agriculture sector for the detection of plant diseases, such as coffee [12] and Enset [13], Crop yield prediction [14], quality and growth monitoring [15,16], supply chain performance [17], and water stress determination [18].

Plants constitute 98% of the world's diet, two-thirds of which are Cereals [19]. The eight major kinds of cereal, wheat, maize, rice, barley, sorghum, oats, millets, and rye cover 56 percent of the world's arable land. Wheat, maize, and rice account for 80% of global cereal production [19]. Plant diseases are the major cause of global crop yield reduction, resulting in 10% loss of all the global food production [20]. The major plant disease-causing pathogens are viruses, bacteria, Oomycetes, fungi, nematodes, and other parasitic plants [20]. When infections occur to a large extent, losses to cereal crop production could reach as high as 50% [21]. Many laboratory techniques are available for the identification and detection of plant pathogens [20], but rapid and early detection is an important factor in the successful containment and control [22]. In this work, we present a survey of machine learning, especially deep learning techniques in the detection of cereal crop diseases.

We placed a special emphasis on the tools and available datasets, which we think are the major hurdles researchers face when planning the undertaking of research work on this area of study.

The rest of the paper is organized into nine sections: In Section 2, we begin by reviewing the latest survey papers performed on machine learning-based plant disease detection and identification. In Section 3, we conduct a detailed discussion on the major cereal crop species and summarise the common and damaging types of diseases affecting each cereal crop. In Section 4, we discuss the methodology and criteria for the selection of works. In Section 5, we provide a detailed discussion on works performed on each cereal crop species, various machine learning approaches, and available datasets.

2. Related Literature Review

In this section, we will discuss the latest survey/review works undertaken on the application of machine learning in the overall field of agriculture—from disease detection to crop growth monitoring. This section contains papers excluded from the reviewed publications according to selection criteria discussed under Section 4.

A review of deep learning and visualization techniques for the detection and classification of plant diseases was discussed by Saleem et al. [23]. The authors discussed the most used deep learning architectures, public datasets, and performance metrics used for the task of plant disease detection.

A systematic literature review on the use of convolutional neural networks for the detection and classification of plant diseases was presented by Abade et al. [24]. The authors reviewed 121 works performed on the area of plant disease detection using deep learning techniques for the past ten years (2010–2019). Based on their systematic survey, the authors identified PlantVillage [25] as the most commonly used dataset and TensorFlow as the commonly used deep learning framework.

A review in the application of machines in the detection of non-destructive defects in horticultural products was discussed by Nturambirwe and Opara [15]. They discussed the most common and damaging types of defects that occur to fruit and vegetable products due to pre and post-harvest practices, handling and storage conditions, and pathogens. The authors conducted a detailed summary of the different types of machine learning algorithms and the various sensing techniques. They concluded that machine learning and deep learning methods have shown a good result in overcoming challenges of effective, objective, and fast detection of defects in horticultural products.

Klompenburg et al. [26] undertook a systematic literature review of 567 studies performed on crop yield prediction. Their work aims at finding the latest algorithms and most common features used for the problem of crop yield prediction using machine learning. From this systematic literature review, they found that temperature, rainfall, and soil type are the most common features, and Artificial Neural Network(ANN) is the most applied algorithm.

Hasan et al. [27] discussed deep learning approaches for the detection and classification of weeds. The authors presented a detailed review of the data acquisition, dataset preparation, deep learning architectures, and evaluation metrics used for the task of detection, classification, and localization of weeds.

Nagaraju et al. [28] performed a systematic review of 84 works of literature on the application of deep learning in plant disease detection. Their review aims at identifying the best datasets for various plants, deep learning models, and pre-processing techniques. They found that most deep learning models are limited in processing original unaltered image data and that an appropriate pre-processing algorithm is required for good model performance.

As it can be observed in Table 1, most of the works conduct a detailed discussion on machine learning approaches for the detection of plant diseases in general and miss out on almost all major cereals. This work attempts to fill in this gap by dedicating the whole content to works conducted on machine learning-based cereal crop detection and identifying all available datasets.

Table 1. Summary.

Citation/Year	Contribution	Limitation
Saleem et al. [23] (2019)	Detailed discussion on the most used deep learning methods for plant disease detection.	Lacks summary of datasets and does not cover major cereal crops.
Abade et al. [24] (2020)	Discussed in detail on deep leaning methods and popular datasets on plant disease detection.	Misses on most cereal crop detection methods and datasets.
Nturambirwe and Opara [15] (2020)	Performed in detail discussion of defects on horticultural products and the different machine learning approaches.	The survey paper does not cover most cereal crops.
Van et al. [26] (2020)	Contains a detailed systematic review of works on crop yield prediction.	This paper does not discuss crop disease detection.

3. Cereal Crops and Diseases

Cereal is a crop closely related to grass and that is cultivated for its seed and is consumed as food by humans [29]. According to the Cereal Disease, Methodology Manual [19], the eight major kinds of cereal, covering 56% percent of the world's arable land are Wheat, Maize, Rice, Barley, Sorghum, Oats, Millet, and Rye.

3.1. Wheat

Wheat is the most dominant and important source of food for humans and livestock [30]. It is the main ingredient in flour, which is used in the making of bread, biscuits, and pastry [19]. Wheat is cultivated across all parts of the earth, from Russia in the northern hemisphere to Argentina in the south [30]. Diseases pose a serious threat to the global production of wheat [20]. Diseases on wheat are caused by a variety of pathogens. These are, Fungai, Viruses, Bacteria, Insects and Nematodes [31]. Some of the commonly occurring wheat diseases are given in Table 2.

Table 2. Some wheat disease types and causing pathogens [31].

Pathogen	Disease
Fungus	Leaf Rust (Brown Rust), Stem Rust (Black Rust), Stripe Rust (Yellow Rust), Common Root Rot, Common and Dwarf Bunt (Stinking Smut), Wheat Blast, Tan Spot
Bacteria	Bacterial Stripe (Black Chaff), Basal Glume Rot and Bacterial Leaf Blight, Bacterial Spike Blight (Gummosis)
Virus	Barley Yellow Dwarf, Barley Stripe Mosaic, Wheat Streak Mosaic

Table 2. *Cont.*

Pathogen	Disease
Insect	Aphids, Stink Bugs, Cereail Leaf Beetle, Thrips, Hessian Fly, Wireworms, Mites
Nematode	Seed Gall Nematode Cereal Cyst Nematode Root Knot Nematode Root Lesion Nematode

3.2. Maize (Corn)

Maize is an important staple food crop that is grown all over the globe. It is the largest grown cereal per unit area, yielding 785 million tons annually [32]. Besides being a source of food, maize, and its products are used as raw materials for many industrial applications. Maize is prone to many types of diseases caused by a variety of pathogens. Fungal pathogens are the major causes of maize disease, while bacterial and viral diseases are less common but pose a serious threat [21,33]. Commonly occurring maize diseases are given in Table 3.

Table 3. Some Maize disease types and causing pathogens [31,33].

Pathogen	Disease
Fungus	Gray leaf spot, Brown spot, Stripe Rust (Yellow Rust) Common rust, Smut, Northernl eaf blight, Southern leaf blight
Bacteria	Corn stunt disease Stewart wilt Bacterial stalk rot Bacterial leaf strip
Virus	Leaf fleek Mosaic Yellow dwarf

3.3. Rice

Rice is the second most-produced cereal crop in the world [34]. It is the main source of food for billions of people in the world and is one of the primary food sources for the majority of people in Asia [35] with around 500 metric tons [36] of rice milled every year. Rice is susceptible to a variety of disease-causing pathogens that attack the leaf, the seed, the stem, and the root [37], some are given in Table 4.

Table 4. Some Rice disease types and causing pathogens [20,37].

Pathogen	Disease
Fungus	Leaf brown spot, Rice blast, Sheath rot Common rust, Northern leaf blight Southern leaf blight, Smut
Bacteria	Bacterial blight
Virus	Rice tungro disease Yellow dwarf

3.4. Barley

Barley is an important staple food cereal crop, although it is produced in much less quantity than wheat, maize, and rice [19]. It is farmed in significant quantities in sub-Saharan countries like Ethiopia [38], where barley adaptation to high altitude environments makes it an important source of food and beverages for millions of people [39]. Barley is affected by over 80 different diseases caused by a variety of pathogens [40]. Some of these are summarized in Table 5.

Table 5. Some Barley disease types and causing pathogens [19,20,40].

Pathogen	**Disease**
Fungus	Stripe rust, Leaf rust, Stem rust Powdery mildew, Downy mildew Net blotch, Spot blotch, Stripe disease
Bacteria	Bacterial blight
Virus	Barley stripe mosaic Cereal tillering virus

3.5. Sorghum

Sorghum is the fifth most important cereal crop after wheat, maize, rice, and barley [41]. It is cultivated around the globe and used as a 0 source of food and energy, when used as a bio-fuel [42]. Sorghum production is highly affected by fungal and viral diseases, at times causing around 28% loss in production [43]. Some commonly occurring sorghum diseases are presented in Tables 6–8.

Table 6. Some Sorghum disease types and causing pathogens [20,43].

Pathogen	**Disease**
Fungus	Anthracnose, Leaf blight, Zonate leaf spot Tar spot, Charcoal rot Rust, Gray leaf spot
Bacteria	Bacterial stripe
Virus	Streak disease

Table 7. Some Oats disease types and causing pathogens [20].

Pathogen	**Disease**
Fungus	Crown rust, Stem rust, Powdery mildew Smut disease, Leaf blight Root rot, Crown rot, Snow mold
Bacteria	Halo blight
Virus	Yellow dwarf Mosaic golden stripe

Table 8. Some Rye disease types and causing pathogens [20].

Pathogen	Disease
Fungus	Snow mold, Brown rust, Ergot Eye spot,Sharp eyespot Powdery mildew, Stem rust, Glume blotch
Virus	Yellow dwarf

4. Methods Adopted to Carry Out the Survey

This review of deep learning methods for the detection of cereal diseases is planned to be performed using systematic literature review (SLR) [44]. SLR underlines a well-defined methodology, for identifying research questions, search strategies for finding the relevant literature, and for specifying the required inclusion and exclusion criteria for selecting the appropriate studies.

4.1. Research Questions

This review paper aims at identifying machine learning methods adopted for the detection of cereal crop diseases. In addition, it is especially aimed at finding the most relevant and state-of-the-art machine learning approaches utilized in the past five years. Thus, the primary research question we plan to answer is:

PRQ: *"What are the state-of-the-art machine learning approaches utilized for the problem of detecting cereal crop diseases in the past 5 years?"*

Secondary questions are also prepared to better help in narrowing down the desired answer to the primary research question. These are:

- SRQ1: What are the most important cereal crop species?
- SRQ2: What are the most damaging and prevalent cereal crops disease?
- SRQ3: What kind of datasets are available?
- SRQ4: What are the primary evaluation metrics used in cereal crops disease detection?
- SRQ5: Which machine learning frameworks are commonly used?

4.2. Search Strategies

To find as many relevant primary studies that aim to answer the primary research question asked, we need to define appropriate search Strategies [44]. Defining a search strategy consists of:

- Selection of electronic search databases;
- Breaking down the research question;
- Drawing up keywords based on synonyms, abbreviations, and alternative spellings [44];
- Constructing Search strings from keywords by using boolean AND's and OR's.

The search strategy of primary studies focuses on publications made on six electronic search databases are: Google Scholar (https://scholar.google.com/ (21 February 2022)), Springer Link (https://link.springer.com/ (21 February 2022)), Science direct (https://sciencedirect.com/ (21 February 2022)), Wiley online library (https://onlinelibrary.wiley.com/ (21 February 2022)), IEEE Xplore (https://ieeexplore.ieee.org/ (21 February 2022)) and MDPI (https://www.mdpi.com/ (21 February 2022)). These databases were selected because of their high impact factor in fields of machine learning. To obtain the most from these electronic search databases, a concise search string must be constructed. A search string is a set of keywords and synonymous terms joined with AND and OR boolean operators because each electronic search database defines its unique syntax. For constructing a search string, we define a generic (pseudo) search string that will be later modified according to each search database. The overall step used for searching relevant works is presented in Algorithm 1 .

(“Wheat” **OR** “Maize” **OR** “Corn” **OR** “Rice” **OR** “Barley” **OR** “Sorghum”) **AND**
(“Disease” **OR** “Disorder” **OR** “Infection”)
AND
(“Machine Learning” **OR** “Deep Learning” **OR** “CNN” **OR** “DNN” **OR** “SVM”)
AND
(“Detection” **OR** “Identification” **OR** “Classification”)

Algorithm 1 Pseudocode for generating search string

```
Databases ← [Google_Scholar, Springer_Link, MDPI, Science_Direct,
Wiley_Online, IEEE_Xplore]
{Initialize keywords}
Cereal_keywords ← [Wheat, Maize, Corn, Rice, Barley, Sorghum]
Disease_keywords ← [Disease, Disorder, Infection]
Tool_keywords ← [Deep_Learning, Machine_Learning, CNN, SVM, DNN]
Aim_keywords ← [Detection, Classification, Identification]
Search_String ← "" {Search string}
for cereal ∈ Cereal_keywords do
  for disease ∈ Disease_keywords do
    for aim ∈ Aim_keywords do
      for tool ∈ Aim_keywords do
        Search_String = cereal AND disease AND aim AND tool
        for database ∈ Databases do
          papers ← databases.search(Search_String)
        end for
      end for
    end for
  end for
end for
```

We applied these search strings to the respective search databases and narrowed down the search results based on the search criteria defined in Table 9. This step gave us the final list of works that fulfil all the criteria’s, Table 10.

Table 9. Selection criteria.

ID	Inclusion	Exclusion	Description
C1	X	-	Studies that approach the identification of cereal crop disease detection through CNN, Deep Learning or any machine learning algorithm.
C2	X	-	Studies performed between the year 2017–2021
C3	X	-	Studies that focus on at least one of the cereal crops
C4	-	X	Duplicate publications
C5	-	X	Studies performed in languages other than English
C6	-	X	Studies that don't use any machine learning or Deep learning methods.

Table 10. Number of documents retrieved for each cereal crop type.

Cereal	Number of Studies	Number of Studies after Applying Criteria
Wheat	29	19
Rice	20	17
Maize	14	9
Barley	2	0
Sorghum	1	0
Rye	0	0

5. Machine Learning-Based Cereal Crop Disease Detection

In this section, we will discuss machine learning approaches utilized for the detection of the listed cereal crop species. We covered works conducted on disease detection from images taken by mobile/digital cameras and hyper-spectral images [45,46] captured by spectral imaging devices. Hyperspectral imagery is a non-invasive technology for extracting spectral, spatial, textural, and contextual features from food and agricultural products [47].

5.1. Machine Learning in Wheat Disease Detection

Bao et al. [48] applied elliptical-maximum margin criterion metric learning to the identification and severity estimation of powdery mildew and stripe wheat disease types. The researchers choose the E-MMC algorithm since it is better suited to finding nonlinear transformations in patterns, and their results show that it achieved superior results when compared to the SVM algorithm. For testing their algorithm, the researchers prepared a dataset from farms around the province of Beijing. In total, they collected 360 images. Disease spot segmentation was performed by using the Otsu thresholding algorithm and feature extraction using HSV histogram, Color moments for color attributes, and LBP and Gabor for texture attributes.

Sood et al. [49] proposed a deep learning approach for the detection of wheat rust disease. The researchers employed the *VGG16* architecture and achieved a classification accuracy of 99.07%. Their work aims at detecting the two types of wheat rust disease, namely Leaf rust and Stem rust. For training the VGG16 model, they used a publicly available dataset collected from various sources such as Kaggle and Google photos. In total, they collected 142 healthy images, 358 Leaf rust, and 376 Stem rust images. Image augmentation was performed to increase the size of the dataset.

Sumit et al. [50] employed the Support Vector Machine (SVM) algorithm for the detection and prevention of fungal wheat leaf diseases. The authors targeted four fungal wheat leaf diseases (Tan spot, Septoria, Pink snow mold, and powdery mildew). Initial segmentation of healthy leaf areas from diseased areas was achieved by using the k-means algorithm.

Mukhtar et al. [51] proposed a one-shot learning approach based on the MobileNet v3 architecture. The pre-trained MobileNet model was further fine-tuned on the PlantVillage dataset and the last two fully connected layers were fine-tuned on a dataset of 440 images consisting of 11 wheat disease classes. Each class has 40 images each. The training dataset is composed of images collected from the CGIAR crop disease dataset and Google Images. The authors used accuracy, precision, and recall as the main performance metrics, and, using their proposed approach, they manage to obtain 92% accuracy, 84% precision, and 85% recall.

An N-CNN based Powdery Mildew wheat disease detection proposed by Kumar et al. [52] uses a CNN that is initially trained on the CGIAR dataset and then utilized a transfer learning approach to increase the model's accuracy on a smaller Powdery Mildew dataset. Their dataset consists of 450 images comprised of images collected on the field by the researchers and also images acquired from sources on the internet. They used the accuracy metrics to measure their model's performance and manage to achieve 89.9% accuracy on testing data.

A Deep Learning approach towards the detection of a wide variety of wheat diseases was proposed by Tagel et al. [53]. The proposed approach employed popular deep learning architectures i.e., Inceptionv3, ResNet50, and VGG16/19. The authors compared the performance of these architectures on a dataset consisting of 1500 images belonging to three classes of wheat diseases. The dataset was compiled from a combination of images collected from wheat farms in Ethiopia and a publicly available online repository.

Classification and detection of 10 classes of wheat disease using VGG16 and ResNet50 architectures were performed by Lakshay et al. [54]. The authors used a Large Wheat Disease Classification Dataset (LWDCD2020) compromising over twelve thousand images belonging to nine wheat disease classes and one healthy class. For evaluation of the proposed model, they utilized accuracy and f1 metrics. The proposed model managed to achieve 98.62% classification accuracy.

An in-field automatic wheat disease diagnosis based on weakly-supervised deep learning was proposed by Jiang et al. [55]. The authors trained two models, VGG-FCN and VGC-FCN-S, using Multiple Instance Learning (MIL). To achieve this, they produce a dataset, Wheat Disease Database 2017 (WDD2017), consisting of 9230 images of wheat crops belonging to six classes of wheat diseases and one healthy class. The two proposed deep learning models achieved a 97.95% and 95.12% accuracy, respectively.

A modified AlexNet architecture was proposed by Hussain et al. [56] for the detection and classification of four types of wheat diseases (Stem rust, Yellow rust, powdery mildew). The authors employed a transfer learning approach, by using a pre-trained AlexNet on the ImageNet dataset and using a custom dataset to further fine-tune the model. The authors collected a dataset of 8828 images divided into 7062 training and 1766 testing sets. The proposed model achieved an accuracy of 84.54%. Wheat leaf rust detection at canopy scale was proposed by Azadbakht et al. [57]. The method investigates four methods, v-Support Vector Regression, boosted Regression Trees, Random Forest Regression, and Gaussian Process Regression for the detection and severity estimation of leaf rust disease.

Identification of various wheat diseases using hyper-spectral image data were performed by [47,58–60]. Identification of wheat powdery mildew disease using linear regression and an SVM (Figure 1) classifier on hyper-spectral data ranging from 656 nm to 784 nm was implemented by Huang et al. [58]. The authors employed the Relief-F algorithm to identify the best spectral bands and evaluation of the SVM algorithm was performed by k-fold cross-validation. In addition, Huang et al. [59] proposed an SVM-based detection of Fusarium Head Blight on wheat heads using hyperspectral imagery. Here, Fishers Linear Discrimination (FLD) was implemented for dimensionality reduction. An in-field detection of yellow rust and fusarium head blight in wheat-based on the ground and UAV-based platforms was discussed by Bohnenkamp et al. [61] (Figure 2) and Xiao et al. [62].

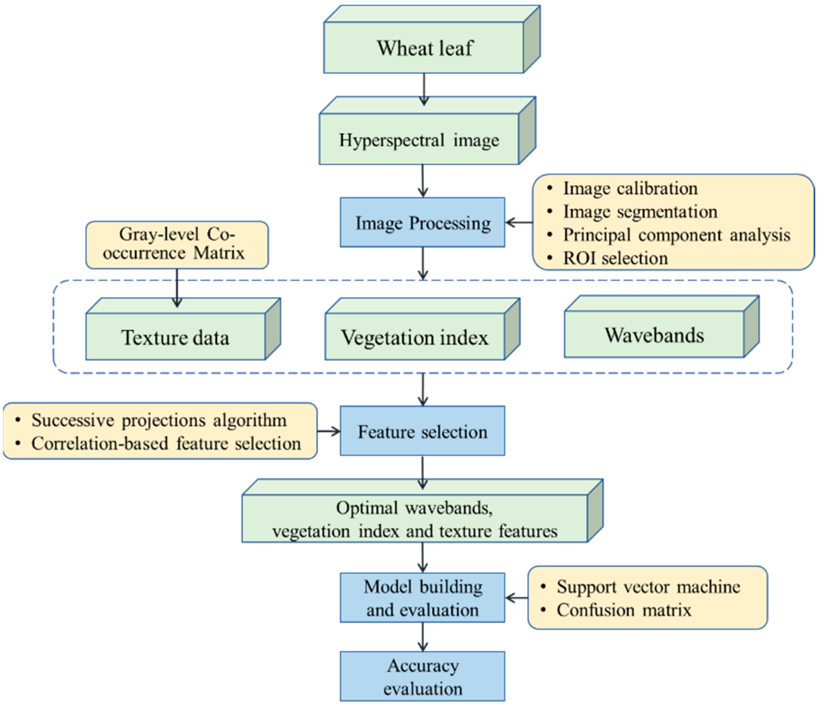

Figure 1. Flow chart for hyper-spectral image data analysis and processing for wheat rust detection [58].

Figure 2. UAV system and photo-bike used for hyperspectral imaging of wheat farms [61].

Summary of various wheat leaf disease datasets is presented in Table 11.

Table 11. Performance comparison of selected studies on machine learning based wheat disease detection and corresponding datasets.

Citatation	Year	Data Type	# of Classes	Sample Size	Method	Accuracy %
Bao et al. [48]	2021	Image	3	360	SVM	93.3%
Sood et al. [49]	2020	Image	3	876	VGG16	99.07%
Mukhtar et al. [51]	2021	Image	11	440	MobileNet	92%
Kumar et.al [52]	2021	Image	1	450	CNN	89.9%
Tagel et al. [53]	2021	Image	3	1500	VGG19	99.38%
Hussain et al. [56]	2018	Image	4	8828	AlexNet	84.54%
Jiang et al. [55]	2017	Image	6	9230	VGG-FCN	97.95%
Azadbakht et al. [57]	2019	Hyper-spectral	2	284	v-SVR	$0.99R^2$
Huang et al. [58]	2019	Hyper-spectral	2	145	Linear Regression	$0.75R^2$
Huang et al. [59]	2019	Hyper-spectral	2	89	SVM	85.7%

5.2. Machine Learning in Rice Disease Detection

Identification and classification of 12 types of rice leaf diseases using MobileNetV2 architecture and attention mechanism were proposed by Chen et al. [63]. The MobileNetV2 architecture was pre-trained on the ImageNet dataset and fine-tuned by using the transfer learning approach on a smaller local dataset. The authors utilized Channel Attention Mechanism (CAM) to better learn the inter-channel relationships. For fine-tuning and testing their proposed model, the authors collected a total of 1100 images of healthy and disease rice leaves. These 660 were compiled from various sources on the internet and 440 were collected from the field. The proposed model achieved an average classification accuracy of 99.67%. Similarly, Wang et al. [64] proposed a MobileNetv2 based approach for the classification of three types of rice leaf diseases by utilizing attention mechanism and Bayesian optimization. Model training and validation were performed on a public dataset of 2370 images belonging to three classes of rice disease and one healthy class. The authors achieved a classification accuracy of 94.65%.

Liang et al. [65] proposed a convolutional neural network-based rice blast disease detection approach. The authors proposed two CNN architectures, the first network containing four convolutional layers, four max-pooling layers, and three fully connected layers, and ReLU after each layer (Figure 3a) and a second network having the same convolutional layers and max-pooling layer structure as the first network, but with two additional fully connected layers as shown in (Figure 3b). The two models were trained on a custom dataset of 5808 images of healthy and rice blast infected leaves. The dataset was collected on-site and is divided into 2906 positive (rice blast infected) and 2902 healthy images. The authors utilized 5-fold cross-validation and a selected the second model due to its inherent stability on small datasets and chieved an accuracy of 95.83%. The proposed approach was compared to hand-crafted approaches like Local Binary Patterns Histogram (LBPH), Haar-WT. The comparison result suggests that the proposed CNN method achieves superior feature extraction and classification results. A similar approach for the detection and classification of three classes of rice disease was proposed by Rahman et al. [66]. The authors proposed a convolutional neural network trained on a dataset of 300 images containing three types of rice leaf disease (Brown spot, Leaf blight, and Hispa) and one healthy class. The model achieved a classification accuracy of 90%. This low classification accuracy is a result of the small dataset size the authors used and the lack of utilizing transfer learning. Ramesh et al. [67] proposed a convolutional neural network approach for the detection of three classes of rice disease. The authors utilized HSV color space for the separation of background and foreground and the K-means algorithm for disease segmentation.

A random forest classifier for the detection and classification of three types of rice leaf disease was proposed by Saha and Ahsan [68]. A local dataset compromising a total of 276 images of healthy and infected rice leaves was collected by the authors for testing and training their proposed algorithm. Feature extraction was implemented by using intensity moments. The proposed approach achieved a classification accuracy of 91.47%.

A deep learning method for the detection of 15 different rice diseases was implemented by Chen et al. [69]. The authors developed a deep learning architecture based on the fusion of existing DenseNet and Inception architectures. For testing the proposed model, the authors compiled a dataset consisting of 500 images belonging to 15 classes of rice disease. Their proposed model achieved a classification accuracy of 94.07%.

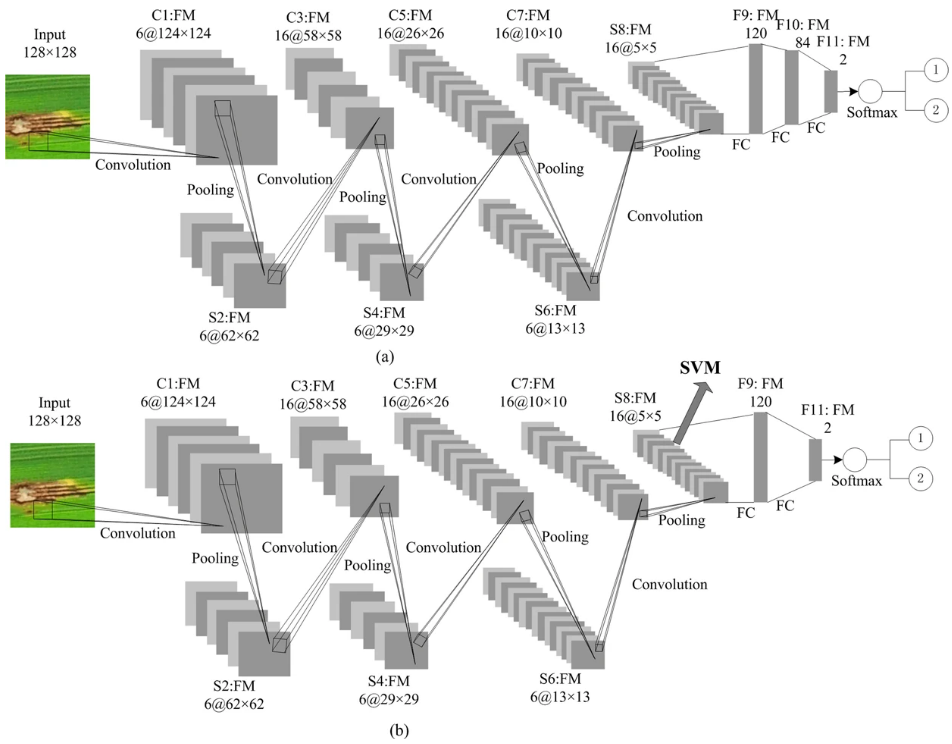

Figure 3. Deep Convolutional Neural Network architecture for the detection of rice blast [65].

Kamrul et al. [70] utilized three popular deep learning architectures for the task of detecting six different types of rice leaf diseases that occur in Bangladesh. They choose the models, Inceptionv3, MobileNetv1, and ResNet50 for their work. They utilized transfer learning and image augmentation techniques. For testing and training their proposed models, the authors collected a dataset of 600 images from rice fields in Bangladesh. Accordingly, they achieved an accuracy of 98%, 99%, and 96% for the models Inceptionv3, MobileNetv1, and ResNet50, respectively. Similarly, Hasan et al. [71] utilized the Inceptionv3 architecture with transfer learning and Support Vector Machine (SVM) for the task of detecting and classifying nine different types of rice disease that occur in Bangladesh. The authors collected a dataset of 1080 images for this task. In this work, Inceptionv3 deep learning model is used for the task of feature extraction and SVM as the final classifier. The authors employed various image processing and augmentation techniques. Their proposed approach gave an accuracy of 97.5%.

Sethy et al. [72] also proposed a deep learning and SVM approach for the detection and classification of four types of rice diseases. In this work, the authors compared and contrasted the performances of 11 different types of deep convolutional neural network architectures that will give the best feature for use with the SVM. For this task, the authors collected a dataset of 5932 images from rice fields around Odisha, India. The performance of the feature extraction CNN models was measured in terms of accuracy, f1, sensitivity, specificity, and training time. Based on their experimental results, the authors found that ResNet50 architecture in conjunction with SVM yields that best classification result of 98.38% and a training time of 69 s.

Zhou et al. [73] proposed a fusion of FCM-KM and Faster R-CNN algorithms for the detection of three distinct rice diseases. FCM-KM was chosen for its tested tolerance for noise and its effectiveness in addressing low detection accuracy caused by background interference and blurred images. For conducting the research, the authors compiled a dataset of 7448 images of rice affected by Rice blast, Bacterial blight, and sheet blight. The Otsu thresholding algorithm was chosen for the task of image segmentation and R-CNN for feature extraction and classification. This approach yielded a classification accuracy of 96.21% with a detection time of 3.22 s per image. A similar Faster R-CNN approach for the detection of Rice False Smut (RFS) was proposed by Sethy et al. [74].

Summary of various rice leaf disease datasets is presented in Table 12.

Table 12. Performance comparison of selected studies on machine learning based rice disease detection and corresponding datasets.

Citatation	Year	Data Type	# of Classes	Sample Size	Method	Accuracy %
Chen et al. [63]	2021	Image	12	1100	MobileNetV2	99.67%
Wang et al. [64]	2021	Image	3	2370	MobileNetV2	94.65%
Liang et al. [65]	2019	Image	1	5808	CNN	95.83%
Rahman et.al [66]	2021	Image	3	300	CNN	90%
Saha and Ahsan. [68]	2021	Image	3	276	CNN	91.47%
Chen et al. [69]	2020	Image	15	500	DenseNet	94.07%
kamrul et al. [70]	2019	Image	2	284	InceptionV3	99%
Hasan et al. [71]	2019	Image	9	1080	InceptionV3	97.5%
Sethy et al. [72]	2020	Image	11	5932	SVM	98.38%
Zhou et al. [73]	2019	Image	3	7448	faster R-CNN	96.21%

5.3. Machine Learning in Maize Disease Detection

An Enhanced CNN for the detection of nine classes of maize leaf disease was proposed by Agarwal et al. [75]. They proposed a convolutional neural network with receptive field enlargement to enhance the feature extraction performance of the CNN, which is required due to the complexity of maize leaf images. To accomplish this task, the authors collected a dataset of 500 images of maize leaves belonging to nine different classes of maize leaf disease at different stages. The performance of the proposed approach was compared to existing models like AlexNet and GoogleNet and provided an improved classification accuracy of 95.12%. Sibiya et al. [76] developed a convolutional neural network for the detection of three different maize leaf diseases by using the Neuroph framework for the java programming language. The proposed approach gave a classification accuracy of 93.5%.

Barman et al. [77] proposed a MobileNet architecture-based maize leaf disease detection that will be deployed on Android mobile devices. The authors utilized a transfer learning approach to fine-tune the pre-trained MobileNet architecture. For this task, they used a public dataset (PlantVillage) with a total of 3852 images of four different classes of maize leaf diseases. The proposed approach yielded an accuracy of 94.53%.

Hasan et al. [78] proposed a hybrid network by combining a convolutional neural network and bi-directional LSTM for the detection of nine classes of maize leaf diseases. bi-LSTM was selected by the authors to better accelerate CNN's classification accuracy and increase the co-relation among extracted features. Training of the model was performed on the PlantVillage dataset, which contains 2500 images of maize leaves affected by nine different types of diseases. They implemented various image augmentation techniques and increased the size of the dataset to 29,065 images. The proposed approach achieved a classification accuracy of 99.02%, exceeding existing deep learning methods.

Xu et al. [79] proposed a multi-scale convolutional global pooling convolutional neural network based on the AlexNet and Inception architecture. The proposed model improves on the AlexNet architecture by replacing the last fully connected layer with a global pooling layer and adding a batch normalization layer. This is implemented to solve the low accuracy achieved and the large training data size required when utilizing transfer learning. Training and testing of the proposed model were performed on the PlantVillage dataset. The authors found that the proposed approach improves average precision by more than 2% when compared to AlexNet. A VGG16 deep learning architecture-based maize disease identification was proposed by Tian [80]. In this work, a transfer learning approach was used to fine-tune the pre-trained VGG16 architecture on a dataset consisting of 7858 images of maize leaves affected by six types of diseases. The proposed method achieved a classification accuracy of 96.8%. Summary of various maize leaf disease datasets is presented in Table 13.

Table 13. Performance comparison of selected studies on machine learning based maize disease detection and corresponding datasets.

Citatation	Year	Data Type	# of Classes	Sample Size	Method	Accuracy %
Agarwal et al. [63]	2021	Image	9	500	CNN	95.12%
Sibiya et al. [76]	2019	Image (PlantVillage)	9	2500	CNN	95.5%
Barman et al. [77]	2021	Image (PlantVillage)	9	2500	MobileNetV2	93.5%
Hasan et al. [78]	2020	Image (PlantVillage)	9	2500	LSTM	99.02%
Xu et al. [79]	2021	Image (PlantVillage)	9	2500	TCI-ALEXN	99.18%
Tian [80]	2019	Image (PlantVillage)	9	2500	VGG16	96.8%

6. Discussion

The past decade has seen the rise of Machine learning applications in various sectors; this exponential rise is attributed to the development of efficient deep learning models for classification and object detection. In our work, we managed to explore research works conducted on the application of machine learning in the area of agriculture, specifically on the application of machine learning techniques in the detection and identification of cereal crop diseases. The survey is conducted on research works performed in the past five years and, as such, we noticed an increase of interest in the research of applying machine learning techniques for cereal crop disease es detection. This is reflected in Figure 4, in which the majority of the works covered in this review paper are performed in the past three years. This rise in research work is attributed to :

- Availability of public datasets
- Availability of efficient and powerful models
- Free cloud computing resources like Google co-laboratory

Our review work has outlined the rapid popularity of Deep Learning techniques (Figure 5) when compared to traditional machine learning algorithms. Deep learning techniques have become a choice for their performance and there flexibility of adapting to unique tasks. The outstanding performance of deep learning techniques in the area of object detection is also one of the factors for their rise in popularity. We also factored in Transfer Learning as one of the major reasons for the increased use of deep learning architectures. Transfer learning allowed researchers to gain the most out of existing architectures by reducing the time needed for training a model and also the need for high-performance computing resources. From our observation and analysis of works conducted on machine learning-based cereal crop disease detection, we summarise the best approaches for the task. These are:

- For early disease detection, Hyperspectral/multispectral imaging in conjunction with deep learning is the appropriate tool. It allows for much earlier disease detection, even before major symptoms arise.
- Deep Learning models trained via transfer learning achieve a better detection/classification performance with a much shorter training time
- Deep Learning models trained on a dataset of images captured using mobile/digital cameras are the preferable option when aiming for an effective and easily deployable solution.

The major challenges we identified during the survey work are:

- Lack of a standardised public dataset;

- The majority of available datasets are limited to certain geographic area.

Cereal	2017	2018	2019	2020	2021
Wheat	2	3	4	2	8
Rice	1	0	5	6	5
Maize	0	0	3	1	5

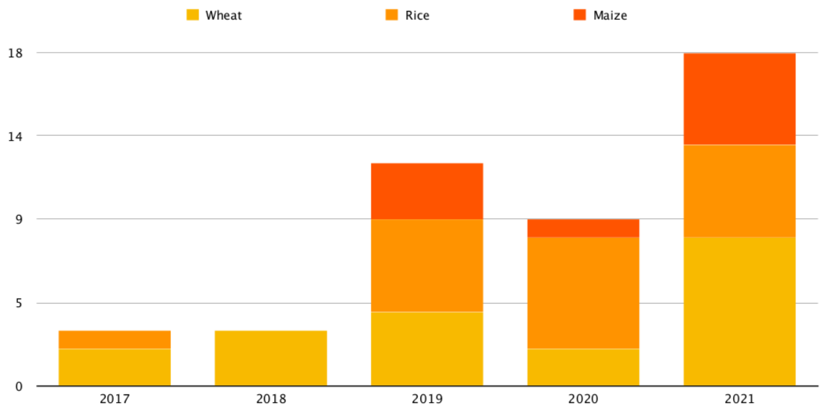

Figure 4. Distribution of research papers by year.

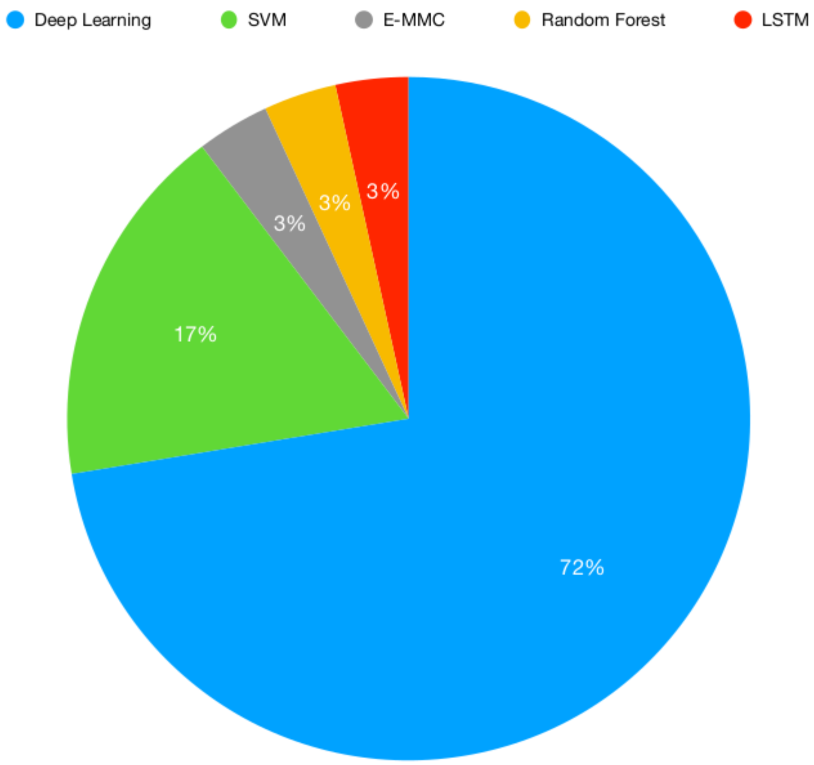

Figure 5. Distribution of machine learning techniques.

7. Conclusions

This systematic literature review tried to investigate the state-of-the-art machine learning applications in cereal crop disease detection. The review was performed on 45 research articles that focus on the application of machine learning in the detection of various diseases that occur on five types of cereal crops i.e., Wheat, Rice, Maize, Barley, and Sorghum. The review includes works published in 2017–2021. For selecting the significance of works, we set out predefined search strategies based on a primary and secondary research question. Works that answer the research questions and pass the selection criterion are selected from five online search databases. With regard to reviewing articles, we tried to identify and summarise the available open datasets available for each category of cereal crops.

Author Contributions: Conceptualization, F.G.W. and T.G.D.; Methodology, F.G.W. and T.G.D.; Validation, Y.M.A. and F.S., T.G.D. and S.R.K.; Writing—original draft preparation, F.G.W.; Writing—review and editing, Y.M.A., F.S., T.G.D. and S.R.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Debelee, T.G.; Kebede, S.R.; Schwenker, F.; Shewarega, Z.M. Deep Learning in Selected Cancers' Image Analysis—A Survey. *J. Imaging* **2020**, *6*, 121. [CrossRef] [PubMed]
2. Rufo, D.D.; Debelee, T.G.; Ibenthal, A.; Gachena, W.G. Diagnosis of diabetes mellitus using gradient boosting machine (LightGBM). *Diagnostics* **2021**, *11*, 1714. [CrossRef]
3. Debelee, T.G.; Amirian, M.; Ibenthal, A.; Palm, G.; Schwenker, F. Classification of mammograms using convolutional neural network based feature extraction. In Proceedings of the International Conference on Information and Communication Technology for Develoment for Africa, Bahir Dar, Ethiopia, 25–27 September 2017; Springer: Cham, Switzerland, 2017; pp. 89–98.
4. Rufo, D.D.; Debelee, T.G.; Gachena, W.G. A Hybrid Machine Learning Model Based on Global and Local Learner Algorithms for Diabetes Mellitus Prediction. *J. Biomim. Biomater. Biomed. Eng.* **2022**, *54*, 65–88. [CrossRef]
5. Biratu, E.S.S.; Schwenker, F.; Debelee, T.G.G.; Kebede, S.R.R.; Negera, W.G.G.; Molla, H.T.T. Enhanced Region Growing for Brain Tumor MR Image Segmentation. *J. Imaging* **2021**, *7*, 22. [CrossRef] [PubMed]
6. Debelee, T.G.; Schwenker, F.; Ibenthal, A.; Yohannes, D. Survey of deep learning in breast cancer image analysis. *Evol. Syst.* **2020**, *11*,143–163. [CrossRef]
7. Debelee, T.G.; Gebreselasie, A.; Schwenker, F.; Amirian, M.; Yohannes, D. Classification of mammograms using texture and cnn based extracted features. *J. Biomim. Biomater. Biomed. Eng.* **2019**, *42*, 79–97. [CrossRef]
8. Rahimeto, S.; Debelee, T.G.; Yohannes, D.; Schwenker, F. Automatic pectoral muscle removal in mammograms. *Evol. Syst.* **2019**, *12*, 519–526. [CrossRef]
9. Kebede, S.R.; Debelee, T.G.; Schwenker, F.; Yohannes, D. Classifier Based Breast Cancer Segmentation. *J. Biomim. Biomater. Biomed. Eng.* **2020**, *47*, 41–61. [CrossRef]
10. Gelana, F.; Yadav, A. Firearm detection from surveillance cameras using image processing and machine learning techniques. In *Smart Innovations in Communication and Computational Sciences*; Springer: Singapore, 2019; pp. 25–34.
11. Debelee, T.G.; Schwenker, F.; Kebede, S.R.; Yohannes, D. Evaluation of modified adaptive k-means segmentation algorithm. *Comput. Vis. Media* **2019**, *5*, 347–361. [CrossRef]
12. Waldamichael, F.G.; Debelee, T.G.; Ayano, Y.M. Coffee disease detection using a robust HSV color-based segmentation and transfer learning for use on smartphones. *Int. J. Intell. Syst.* **2011**. [CrossRef]
13. Kibru, Y.; Debelee, T. Detection of Bacterial Wilt on Enset Crop Using Deep Learning Approach. *Int. J. Eng. Res. Afr.* **2020**, *51*, 131–146.
14. Chlingaryan, A.; Sukkarieh, S.; Whelan, B. Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. *Comput. Electron. Agric.* **2018**, *151*, 61–69. [CrossRef]
15. Nturambirwe, J.F.I.; Opara, U.L. Machine learning applications to non-destructive defect detection in horticultural products. *Biosyst. Eng.* **2020**, *189*, 60–83. [CrossRef]
16. Rasti, S.; Bleakley, C.J.; Holden, N.; Whetton, R.; Langton, D.; O'Hare, G. A Survey of High Resolution Image Processing Techniques for Cereal Crop Growth Monitoring. *Inf. Process. Agric.* **2021**. [CrossRef]
17. Sharma, R.; Kamble, S.S.; Gunasekaran, A.; Kumar, V.; Kumar, A. A systematic literature review on machine learning applications for sustainable agriculture supply chain performance. *Comput. Oper. Res.* **2020**, *119*, 104926. [CrossRef]
18. Virnodkar, S.S.; Pachghare, V.K.; Patil, V.; Jha, S.K. Remote sensing and machine learning for crop water stress determination in various crops: A critical review. *Precis. Agric.* **2020**, *21*, 1121–1155. [CrossRef]
19. Stubbs, R.; Prescott, J.; Saari, E.; Dubin, H. Cereal Disease Methodology Manual. 1986. Available online: http://hdl.handle.net/10883/3997 (accessed on 21 February 2022).
20. Strange, R.N.; Scott, P.R. Plant disease: A threat to global food security. *Annu. Rev. Phytopathol.* **2005**, *43*, 83–116. [CrossRef]
21. Różewicz, M.; Wyzińska, M.; Grabiński, J. The Most Important Fungal Diseases of Cereals—Problems and Possible Solutions. *Agronomy* **2021**, *11*, 714. [CrossRef]
22. Schaad, N.W.; Frederick, R.D.; Shaw, J.; Schneider, W.L.; Hickson, R.; Petrillo, M.D.; Luster, D.G. Advances in molecular-based diagnostics in meeting crop biosecurity and phytosanitary issues. *Annu. Rev. Phytopathol.* **2003**, *41*, 305–324. [CrossRef]
23. Saleem, M.H.; Potgieter, J.; Arif, K.M. Plant disease detection and classification by deep learning. *Plants* **2019**, *8*, 468. [CrossRef]

24. Abade, A.S.; Ferreira, P.A.; Vidal, F.d.B. Plant Diseases recognition on images using Convolutional Neural Networks: A Systematic Review. *arXiv* **2020**, arXiv:2009.04365.
25. Hughes, D.; Salathé, M. An open access repository of images on plant health to enable the development of mobile disease diagnostics. *arXiv* **2015**, arXiv:1511.08060.
26. Van Klompenburg, T.; Kassahun, A.; Catal, C. Crop yield prediction using machine learning: A systematic literature review. *Comput. Electron. Agric.* **2020**, *177*, 105709. [CrossRef]
27. Hasan, A.M.; Sohel, F.; Diepeveen, D.; Laga, H.; Jones, M.G. A survey of deep learning techniques for weed detection from images. *Comput. Electron. Agric.* **2021**, *184*, 106067. [CrossRef]
28. Nagaraju, M.; Chawla, P. Systematic review of deep learning techniques in plant disease detection. *Int. J. Syst. Assur. Eng. Manag.* **2020**, *11*, 547–560. [CrossRef]
29. Barton, S. CEREALS | Grain Defects. In *Encyclopedia of Grain Science*; Wrigley, C., Ed.; Elsevier: Oxford, UK, 2004; pp. 223–228. [CrossRef]
30. Shewry, P.R. Wheat. *J. Exp. Bot.* **2009**, *60*, 1537–1553. [CrossRef]
31. Duveiller, E.; Singh, R.; Singh, P.; Dababat, A.; Mezzalama, M. Wheat Diseases and Pests: A Guide for Field Identification. 2012. Available online: http://hdl.handle.net/10883/1115 (accessed on 21 February 2022).
32. Orhun, G.E. Maize for life. *Int. J. Food Sci. Nutr. Eng.* **2013**, *3*, 13–16.
33. Subedi, S. A review on important maize diseases and their management in Nepal. *J. Maize Res. Dev.* **2015**, *1*, 28–52. [CrossRef]
34. Van Nguyen, N.; Ferrero, A. Meeting the Challenges of Global Rice Production. *Paddy Water Environ.* **2006**, *4*, 1–9. [CrossRef]
35. Yoshida, S. *Fundamentals of Rice Crop Science*; International Rice Research Institute: Los Baños, Philippines, 1981.
36. Muthayya, S.; Sugimoto, J.D.; Montgomery, S.; Maberly, G.F. An overview of global rice production, supply, trade, and consumption. *Ann. N. Y. Acad. Sci.* **2014**, *1324*, 7–14. [CrossRef]
37. Phadikar, S.; Sil, J.; Das, A.K. Rice diseases classification using feature selection and rule generation techniques. *Comput. Electron. Agric.* **2013**, *90*, 76–85. [CrossRef]
38. Bekele, B.; Alemayehu, F.; Lakew, B. Food barley in Ethiopia. In *Food Barley: Importance, Uses, and Local Knowledge*; ICARDA: Aleppo, Syria, 2005; pp. 53–82.
39. Mulatu, B.; Grando, S. *Barley Research and Development in Ethiopia*; EIAR: Addis Ababa, Ethiopia. 2011.
40. Paulitz, T.C.; Steffenson, B.J. Biotic stress in barley: Disease problems and solutions. In *Barley Production, Improvement, and Uses*; John Wiley & Sons, Inc.: Hoboken, NJ, USA, 2011; pp. 307–354.
41. Ramatoulaye, F.; Mady, C.; Fallou, S. Production and use sorghum: A literature review. *J. Nutr. Health Food Sci.* **2016**, *4*, 1–4.
42. Rooney, W.L. Sorghum. In *Cellulosic Energy Cropping Systems*; John Wiley & Sons: Hoboken, NJ, USA, **2014**; pp. 109–129.
43. Pande, S.; Harikrishnan, R.; Alegbejo, M.; Mughogho, L.; Karunakar, R.; Ajayi, O. Prevalence of sorghum diseases in Nigeria. *Int. J. Pest Manag.* **1993**, *39*, 297–303. [CrossRef]
44. Keele, S. Guidelines for Performing Systematic Literature Reviews in Software Engineering. Technical Report. 2007. Available online: https://www.researchgate.net/publication/302924724_Guidelines_for_performing_Systematic_Literature_Reviews_in_Software_Engineering (accessed on 21 February 2022).
45. Luo, F.; Zou, Z.; Liu, J.; Lin, Z. Dimensionality Reduction and Classification of Hyperspectral Image via Multistructure Unified Discriminative Embedding. *IEEE Trans. Geosci. Remote Sens.* **2022**, *60*, 1–16. [CrossRef]
46. Luo, F.; Huang, H.; Ma, Z.; Liu, J. Semisupervised Sparse Manifold Discriminative Analysis for Feature Extraction of Hyperspectral Images. *IEEE Trans. Geosci. Remote Sens.* **2016**, *54*, 6197–6211. [CrossRef]
47. Guo, A.; Huang, W.; Ye, H.; Dong, Y.; Ma, H.; Ren, Y.; Ruan, C. Identification of wheat yellow rust using spectral and texture features of hyperspectral images. *Remote Sens.* **2020**, *12*, 1419. [CrossRef]
48. Bao, W.; Zhao, J.; Hu, G.; Zhang, D.; Huang, L.; Liang, D. Identification of wheat leaf diseases and their severity based on elliptical-maximum margin criterion metric learning. *Sustain. Comput. Inform. Syst.* **2021**, *30*, 100526. [CrossRef]
49. Sood, S.; Singh, H. An implementation and analysis of deep learning models for the detection of wheat rust disease. In Proceedings of the 2020 3rd International Conference on Intelligent Sustainable Systems (ICISS), Thoothukudi, India, 3–5 December 2020; pp. 341–347.
50. Nema, S.; Dixit, A. Wheat leaf detection and prevention using support vector machine. In Proceedings of the 2018 International Con ference on Circuits and Systems in Digital Enterprise Technology (ICCSDET), Kottayam, India, 21–22 December 2018; pp. 1–5.
51. Mukhtar, H.; Khan, M.Z.; Khan, M.U.G.; Younis, H. Wheat Disease Recognition through One-shot Learning using Fields Images. In Proceedings of the 2021 International Conference on Artificial Intelligence (ICAI), Islamabad, Pakistan, 5–7 April 2021; pp. 229–233.
52. Kumar, D.; Kukreja, V. N-CNN Based Transfer Learning Method for Classification of Powdery Mildew Wheat Disease. In Proceedings of the 2021 International Conference on Emerging Smart Computing and Informatics (ESCI), Pune, India, 5–7 March 2021; pp. 707–710.
53. Aboneh, T.; Rorissa, A.; Srinivasagan, R.; Gemechu, A. Computer Vision Framework for Wheat Disease Identification and Classification Using Jetson GPU Infrastructure. *Technologies* **2021**, *9*, 47. [CrossRef]
54. Goyal, L.; Sharma, C.M.; Singh, A.; Singh, P.K. Leaf and spike wheat disease detection & classification using an improved deep convolutional architecture. *Inform. Med. Unlocked* **2021**, *25*, 100642.

55. Lu, J.; Hu, J.; Zhao, G.; Mei, F.; Zhang, C. An in-field automatic wheat disease diagnosis system. *Comput. Electron. Agric.* **2017**, *142*, 369–379. [CrossRef]
56. Hussain, A.; Ahmad, M.; Mughal, I.A. Automatic Disease Detection in Wheat Crop using Convolution Neural Network. In Proceedings of the 4th International Conference on Next, Generation Computing, Dehradun, India, 21–22 November 2018 .
57. Azadbakht, M.; Ashourloo, D.; Aghighi, H.; Radiom, S.; Alimohammadi, A. Wheat leaf rust detection at canopy scale under different LAI levels using machine learning techniques. *Comput. Electron. Agric.* **2019**, *156*, 119–128. [CrossRef]
58. Huang, L.; Ding, W.; Liu, W.; Zhao, J.; Huang, W.; Xu, C.; Zhang, D.; Liang, D. Identification of wheat powdery mildew using in-situ hyperspectral data and linear regression and support vector machines. *J. Plant Pathol.* **2019**, *101*, 1035–1045. [CrossRef]
59. Huang, L.; Wu, Z.; Huang, W.; Ma, H.; Zhao, J. Identification of fusarium head blight in winter wheat ears based on fisher's linear discriminant analysis and a support vector machine. *Appl. Sci.* **2019**, *9*, 3894. [CrossRef]
60. Khan, I.H.; Liu, H.; Li, W.; Cao, A.; Wang, X.; Liu, H.; Cheng, T.; Tian, Y.; Zhu, Y.; Cao, W.; et al. Early Detection of Powdery Mildew Disease and Accurate Quantification of Its Severity Using Hyperspectral Images in Wheat. *Remote Sens.* **2021**, *13*, 3612. [CrossRef]
61. Bohnenkamp, D.; Behmann, J.; Mahlein, A.K. In-field detection of yellow rust in wheat on the ground canopy and UAV scale. *Remote Sens.* **2019**, *11*, 2495. [CrossRef]
62. Xiao, Y.; Dong, Y.; Huang, W.; Liu, L.; Ma, H. Wheat Fusarium Head Blight Detection Using UAV-Based Spectral and Texture Features in Optimal Window Size. *Remote Sens.* **2021**, *13*, 2437. [CrossRef]
63. Chen, J.; Zhang, D.; Zeb, A.; Nanehkaran, Y.A. Identification of rice plant diseases using lightweight attention networks. *Expert Syst. Appl.* **2021**, *169*, 114514. [CrossRef]
64. Wang, Y.; Wang, H.; Peng, Z. Rice diseases detection and classification using attention based neural network and bayesian optimization. *Expert Syst. Appl.* **2021**, *178*, 114770. [CrossRef]
65. Liang, W.j.; Zhang, H.; Zhang, G.f.; Cao, H.x. Rice blast disease recognition using a deep convolutional neural network. *Sci. Rep.* **2019**, *9*, 1–10. [CrossRef]
66. Rahman, M.A.; Shoumik, M.S.N.; Rahman, M.M.; Hena, M.H. Rice Disease Detection Based on Image Processing Technique. In *Smart Trends in Computing and Communications: Proceedings of SmartCom 2020*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 135–145.
67. Ramesh, S.; Vydeki, D. Rice Disease Detection and Classification Using Deep Neural Network Algorithm. In *Micro-Electronics and Telecommunication Engineering*; Springer: Singapore, 2020; pp. 555–566.
68. Saha, S.; Ahsan, S.M.M. Rice Disease Detection using Intensity Moments and Random Forest. In Proceedings of the 2021 International Conference on Information and Communication Technology for Sustainable Development (ICICT4SD), Dhaka, Bangladesh, 27–28 February 2021; pp. 166–170.
69. Chen, J.; Zhang, D.; Nanehkaran, Y.A.; Li, D. Detection of rice plant diseases based on deep transfer learning. *J. Sci. Food Agric.* **2020**, *100*, 3246–3256. [CrossRef]
70. Kamrul, M.H.; Paul, P.; Rahman, M. Machine vision based rice disease recognition by deep learning. In Proceedings of the 2019 22nd International Conference on Computer and Information Technology (ICCIT), Dhaka, Bangladesh, 18–20 December 2019; pp. 1–6.
71. Hasan, M.J.; Mahbub, S.; Alom, M.S.; Nasim, M.A. Rice disease identification and classification by integrating support vector machine with deep convolutional neural network. In Proceedings of the 2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT), Dhaka, Bangladesh, 3–5 May 2019; pp. 1–6.
72. Sethy, P.K.; Barpanda, N.K.; Rath, A.K.; Behera, S.K. Deep feature based rice leaf disease identification using support vector machine. *Comput. Electron. Agric.* **2020**, *175*, 105527. [CrossRef]
73. Zhou, G.; Zhang, W.; Chen, A.; He, M.; Ma, X. Rapid detection of rice disease based on FCM-KM and faster R-CNN fusion. *IEEE Access* **2019**, *7*, 143190–143206. [CrossRef]
74. Sethy, P.K.; Barpanda, N.K.; Rath, A.K.; Behera, S.K. Rice false smut detection based on faster R-CNN. *Indones. J. Electr. Eng. Comput. Sci.* **2020**, *19*, 1590–1595. [CrossRef]
75. Agarwal, R.; Sharma, H. Enhanced Convolutional Neural Network (ECNN) for Maize Leaf Diseases Identification. In *Smart Innovations in Communication and Computational Sciences*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 297–307.
76. Sibiya, M.; Sumbwanyambe, M. A computational procedure for the recognition and classification of maize leaf diseases out of healthy leaves using convolutional neural networks. *AgriEngineering* **2019**, *1*, 119–131. [CrossRef]
77. Barman, U.; Sahu, D.; Barman, G.G. A Deep Learning Based Android Application to Detect the Leaf Diseases of Maize. In *Proceedings of the Sixth International Conference on Mathematics and Computing*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 275–286.
78. Hasan, M.J.; Alom, M.S.; Dina, U.F.; Moon, M.H. Maize Diseases Image Identification and Classification by Combining CNN with Bi-Directional Long Short-Term Memory Model. In Proceedings of the 2020 IEEE Region 10 Symposium (TENSYMP), Dhaka, Bangladesh, 5–7 June 2020; pp. 1804–1807.

79. Xu, Y.; Zhao, B.; Zhai, Y.; Chen, Q.; Zhou, Y. Maize Diseases Identification Method Based on Multi-Scale Convolutional Global Pooling Neural Network. *IEEE Access* **2021**, *9*, 27959–27970. [CrossRef]
80. Tian, J.; Zhang, Y.; Wang, Y.; Wang, C.; Zhang, S.; Ren, T. A method of corn disease identification based on convolutional neural network. In Proceedings of the 2019 12th International Symposium on Computational Intelligence and Design (ISCID), Hangzhou, China, 14–15 December 2019; Volume 1, pp. 245–248.