applied sciences

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Smart Agriculture Applications Using Deep Learning Technologies: A Survey

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Abstract: Agriculture is considered an important field with a significant economic impact in several countries. Due to the substantial population growth, meeting people's dietary needs has become a relevant concern. The transition to smart agriculture has become inevitable to achieve these food security goals. In recent years, deep learning techniques, such as convolutional neural networks (CNN) and recurrent neural networks (RNN), have been intensely researched and applied in various fields, including agriculture. This study analyzed the recent research articles on deep learning techniques in agriculture over the previous five years and discussed the most important contributions and the challenges that have been solved. Furthermore, we investigated the agriculture parameters being monitored by the internet of things and used them to feed the deep learning algorithm for analysis. Additionally, we compared different studies regarding focused agriculture area, problems solved, the dataset used, the deep learning model used, the framework used, data preprocessing and augmentation method, and results with accuracy. We concluded in this survey that although CNN provides better results, it lacks in early detection of plant diseases. To cope with this issue, we proposed an intelligent agriculture system based on a hybrid model of CNN and SVM, capable of detecting and classifying plant leaves disease early.

Keywords: precision agriculture; smart farming; deep learning; CNN; RNN; SVM

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Citation: Altalak, M.; Ammad uddin, M.; Alajmi, A.; Rizg, A. Smart Agriculture Applications Using Deep Learning Technologies: A Survey. *Appl. Sci.* **2022**, *12*, 5919. https://doi.org/10.3390/app12125919

Academic Editor: Minjuan Wang

Received: 17 April 2022
Accepted: 29 May 2022
Published: 10 June 2022

1. Introduction

Smart agriculture refers to the broad application of artificial intelligence (AI), which involves big data, the internet of things (IoT), deep learning, and many other digital technologies [1]. As the world population grows [2], a significant increase in food production must be realized [3]. Ensuring the constant and consistent availability and quality of food globally without affecting natural ecosystems is challenging for modern technologies. Deep learning is a new cutting-edge technology for image processing and data analysis. It has yielded promising results, possesses enormous potential, and has been successfully employed in various fields, including agriculture [4].

In recent years, deep learning-based agricultural applications (smart agriculture) have achieved tremendous success; this concerns managing different agrarian activities using data acquired from diverse sources. Various intelligent systems based on AI differ in their ability to record and interpret data and assist the farmers in making the right decisions at the right time. Data can be recorded using installed IoT nodes (sensors), processed by any deep learning method, and imposed decisions on operational areas through actuators. Other state-of-the-art technologies, such as remote sensing geographic information, global satellite positioning, and automated computer control, augment the AI system in monitoring and managing agriculture in real-time.

Furthermore, AI-based smart agriculture can be utilized to schedule optimum resources such as fertilizer, pesticides, and water, thereby minimizing pollution and operational/ production costs and maximizing production. As AI can assist in the early detection and prevention of plant diseases, halting their spread would require the application of fewer medications; this reduces environmental contamination significantly [5]. The continuous provision of agronomic inputs, such as water, nutrients, and fertilizers, is critical for plant health, growth, and yield [6]. The absence of any of these inputs may cause biotic and abiotic stress. The decision to apply the right amount of a particular resource at the right time by considering the current situation and future predictions is possible only through AI. This research studied the utilization of AI and deep learning in agriculture and its future potential. We also investigated the agricultural parameters monitored by IoTs and used them to feed the deep learning algorithms for further processing.

This paper presents a survey of newly developed systems in smart agriculture using deep learning techniques. The motivation for preparing this survey stems from the importance of deep learning applications and innovative solutions that deep learning techniques can provide in solving agricultural problems. The use of deep learning techniques in smart agriculture is relatively recent and in the process of progress and continuously gaining popularity in recent publications. Therefore, we have highlighted the contributions made by deep learning techniques to address the problems of smart agriculture in data processing and decision making. One of the main issues we found while surveying the recent research studies is the lack of early detection and classification of plant leaf diseases. We present a proposed system for solving this issue using a hybrid deep learning model based on a convolutional neural network and a support vector machine.

The rest of this paper is structured as follows. The research methodology is explained in Section 2, and Section 3 briefly introduces the deep learning technology, and its applications are discussed in Section 4. Units 5 provides the technical analysis of studied papers, while detailed discussions are given in Section 6. The shortcomings found in this survey are mitigated by proposing a new hybrid system provided in Section 7. Finally, this article is concluded in Section 8.

2. Materials and Methods

In recent years, smart agriculture has flourished in several areas. Furthermore, deep learning applications in smart agriculture have spread widely and yielded advanced, satisfactory results. This paper intends to survey and analyze deep learning techniques and their applications in agriculture to be a modern and comprehensive reference for researchers.

This survey work is conducted in three steps. The first step involved collecting relevant research by searching keywords (agriculture, deep learning, convolutional neural networks, recurrent neural networks, crop monitoring, disease detection, and irrigation systems). Keyword-based searches were performed for journal and conference papers from the IEEE Xplore and ScienceDirect scientific databases and the Web of Science and Google Scholar scientific indexing services. A total of 70 articles were collected that were later reduced to 60, which presented some deep learning models. We studied these papers and further narrowed the numbers to 40 papers that conducted deep learning experiments and provided some results. In the second step, the selected scientific papers were analyzed and compared in terms of:

- The areas of smart agriculture that were focused on.
- The problems that they tried to solve.
- The deep learning techniques and models used.
- The dataset used.
- The data preprocessing and data augmentation methods that were used.
- The results in terms of accuracy or precision.

In the third and last stage, we found that some weaknesses and shortcomings existed in surveyed papers, and we tried to suggest some improvements to overcome these issues.

As an output of this survey, we proposed a hybrid deep learning model consisting of CNN and SVM that is expected to improve existing models' performance and working range.

3. Deep Learning

Deep learning is a subset of machine learning and AI, and is essentially a neural network with three or more layers. These neural networks aim to mimic the activity of the human brain; however, they fall far short of the human brain's ability to learn from large amounts of data. While a single-layer neural network can provide approximate predictions, additional hidden layers can aid in optimizing and refining the accuracy. Machine learning is a subfield of AI that allows the system to learn from concepts and knowledge without being explicitly programmed. It begins with observations, such as face-to-face interactions, to prepare for data features and trends and improve future results and judgments. Deep learning is built on a combination of machine learning algorithms that use multiple nonlinear transformations to model high-level abstractions in data [7]. Feature learning, or the automatic extraction of features from raw data, is a significant advantage of deep learning. Features from higher hierarchy levels are produced by the composition of lower-level components [8]. Recurrent neural network (RNN) and convolutional neural network (CNN) are two standard deep learning networks used in agriculture.

3.1. Convolutional Neural Network (CNN)

A CNN is a deep learning algorithm composed of multiple convolutional layers, pooling layers, and fully connected layers [9]. It is a multi-layer neural network based on the animal visual cortex [10]. CNNs are mainly used for image processing and handwritten character recognition. In several computer vision studies, CNNs have been used for image classification, object detection, fragmentation of images, voice recognition, text and video processing, and medical image analysis, among other functions. A CNN architecture typically consists of convolutional, pooling, and fully connected layers [11]. Figure 1 illustrates the architecture of CNNs, and the layers are explained briefly:

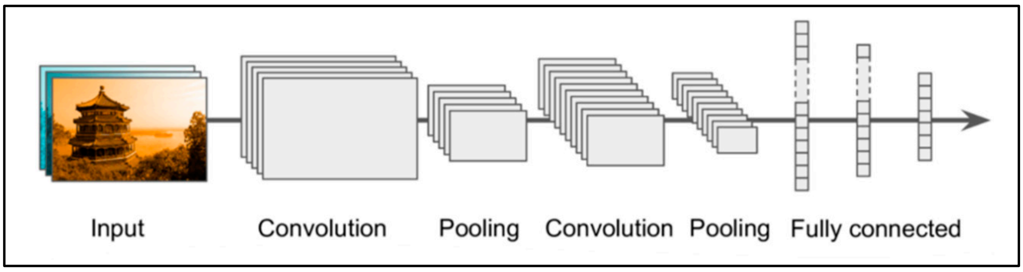

Figure 1. CNN architecture.

3.1.1. Convolutional Layer

The convolutional layer is the most basic and the most significant in a CNN. The resulting pixel matrix for the supplied picture or object is twisted or multiplied to build an activation map for the given image. The activation map's main advantage is that it stores all of the distinguishing qualities of a given image while limiting the amount of data that must be processed simultaneously. The data is combined in a features detector matrix, and various image variants are created by employing different feature detector levels. The convoluted model is also trained with backpropagation to achieve the lowest possible error in each layer. The depth and padding are determined by the error set with the fewest errors [11]. The convolutional layer is responsible for extracting visual features.

3.1.2. Pooling Layer

It is a crucial phase that attempts to minimize the dimensions of the activation map further while simultaneously maintaining only the essential features and minimizing the remarkable invariance. It, in turn, reduces the number of learnable features in the model, thereby contributing to addressing the overfitting issue. Pooling allows a CNN to aggregate all the various dimensions of an image to recognize the supplied object even if the form is warped or at a different angle. Pooling can be carried out in multiple ways, including max pooling, average pooling, stochastic pooling, and spatial pyramid. The most frequent method used is max pooling [11].

3.1.3. Fully Connected Layer

This is the final layer where the neural network is fed. In general, the matrix is flattened before being handed over to the neurons. Data are difficult to follow after this point due to numerous hidden layers with changing weights for each neuron's output. All data reasoning and computing occur here [11].

3.2. Recurrent Neural Network (RNN)

An RNN is a neural sequence model that performs exceptionally well on crucial tasks such as language modeling, speech recognition, and machine translation [12]. RNNs, as opposed to traditional neural networks, take advantage of the network's sequential information; this attribute is critical in many applications where the structure inherent in the data sequence contains valuable information. For instance, to understand a word in a sentence, you must first understand the context. Hence, an RNN can be considered a short-term memory unit that consists of the input layer x, the hidden (state) layer s, and the output layer y [10]. Figure 2 depicts the generic structure of an RNN. Long short-term memory (LSTM) is an RNN architecture built to simulate temporal sequences and their long-term relationships with more precision than ordinary RNNs [13]. Figure 3 depicts the LSTM architecture.

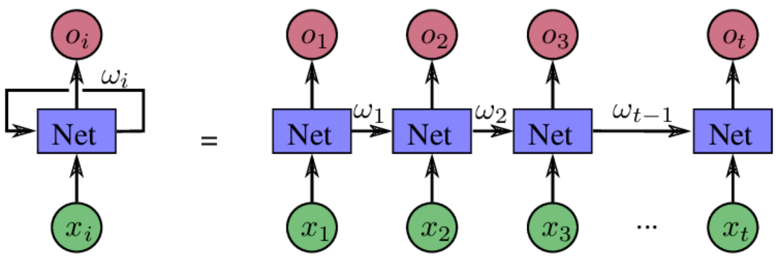

Figure 2. The generic structure of RNN.

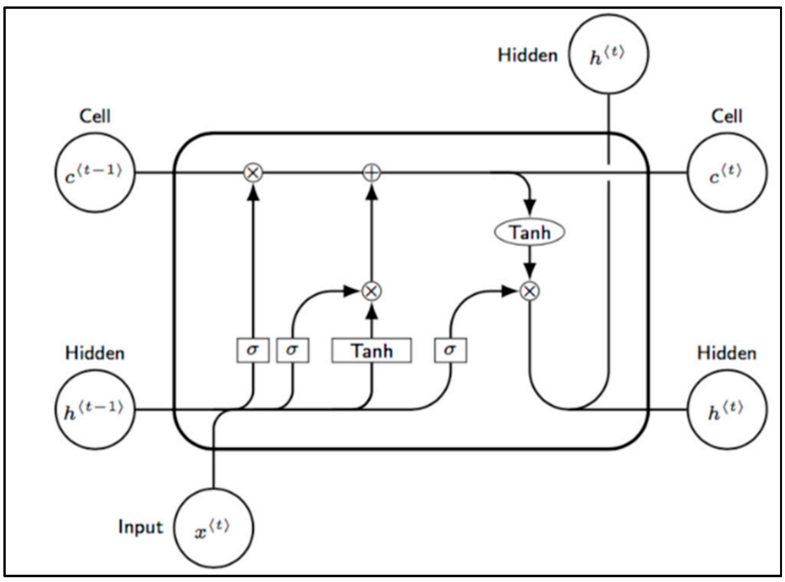

Figure 3. The architecture of LSTM.

4. Applications of Deep Learning in Agriculture

Deep learning algorithms are being used in smart agriculture to monitor various related parameters and observe them from anywhere in the world. We have found in recent surveys that mainly they studied the benefit of deep learning in any one of the agricultural applications. In this survey, we have given an overview of the contributions of deep learning in the different known applications of smart agriculture. We tried to analyze which deep learning model is suitable for which applications and which one is more efficient and effective, among others. We have noticed that researchers' interest is increasing in using the CNN algorithm in plant disease detection and classification applications, and it has given tremendous results.

Weather forecasting applications also use the CNN algorithm very frequently because it is based on time series and offers effective results. We investigated the different areas of smart agriculture and the applications in which deep learning is applied. Our findings are summarized in Table 1.

4.1. Identification/Classification of Plant Disease

Disease fungus, microbes, and bacteria obtain energy from the plants on which they dwell, affecting crop productivity. If not diagnosed in time, this can cause significant economic losses for farmers. Pesticides used to remove pathogens and restore crop functionality impose substantial financial pressures on farmers. Excessive pesticide usage also results in environmental degradation and affects agricultural areas' water and soil cycle [14]. Moreover, plant diseases impact the growth of particular species; hence, early detection of such stress is critical. Many deep learning models (DL) have been deployed to identify and classify plant diseases. Deep learning appears to possess considerable potential in terms of its increasing accuracy over time. Many new DL architectures and improvements/modifications to existing ones are proposed. Various modern visualization techniques are being used to identify and classify the symptoms of plant illnesses [15].

In [16], the author provided a method for identifying and classifying banana diseases based on the CNN model. It can assist the farmers in detecting the attacking illness in a timely, affordable, and swift manner. This system could detect two banana diseases, Sigatoka and speckle, by capturing a photo of an affected leaf and using a deep neural networks model. The authors of [17] used another deep learning model (AlexNet) to classify the type of disease in plants through the leaves pictures with high accuracy of results. A deep learning hybrid model is presented in [18] to classify the sunflower illnesses, including Alternaria leaf rot, Downy mildew, phoma rot, and verticillium wilt. The author utilized the stacking ensemble learning technique to develop a hybrid model of H.VGG-16 and MobileNet. They built their dataset using google photos, and their proposed model provided an accuracy of 89.2%, which they claimed was better than other models.

The research presented in [19] studied and compared the results of five different deep learning models, including H. Vgg16, Vgg19, ResNet50, ResNet50V2, and ResNet101V2, using both simulated data and images obtained from rice fields in the city of Gujranwala located in Pakistan. The ResNet50 model used an artificial dataset and was given accuracy of 75 %, while the ResNet101V2 model had an accuracy of 86.799 on the actual dataset.

The author of [20] developed a machine learning-enabled mobile device for automating the diagnosis of plant leaf diseases. The developed system can classify 38 different types of illness using CNNs as the underlying deep learning engine. The researchers gathered an image dataset containing 96,206 photos of plant leaves from healthy and sick plants for the CNN model's training, validation, and testing. The user interface was created as an Android mobile application that farmers could use to photograph sick plant leaves. The disease category was then displayed, along with the 90 % confidence. This technique is meant to provide farmers with greater chances of keeping their crops healthy and avoiding the excessive use of fertilizers that are harmful to the crops.

In paper [21], a transfer learning pre-trained deep neural network model was used for crop disease prediction to learn essential functions such as leaf characteristics directly from the input data. They investigated various CNN topologies (ResNet, MobileNet, Wide ResNet, and DenseNet) and deep learning methodologies. The results revealed that the suggested method outperforms earlier methods in terms of memory and precision.

Another CNN technique to detect, classify and identify plant disease is presented in [22]. It has proved output result accuracy ranging from 91 to 98 % and an average performance of 96.3% for thirteen different plant diseases. It can also differentiate between healthy and unhealthy leaves and distinguish them from their backgrounds. The author of [23] used a CNN model in agriculture to recognize and classify plant images and achieved the highest accuracy of 99.58 %. They employed off-the-shelf ConvNet representations to evaluate the plant growth of a maize crop.

SVM classifier is proposed in [24], which involves an autonomous plant disease identification using image analysis with a 94 % accuracy. The experiment was carried out with a dataset of 500 plant leaf images taken from thirty different native plant species.

The other deep learning studies such as [25–35] developed automatic plant detection and recognition systems to classify nine different diseases by defining a single healthy class. All these studies employed the PlanVillage dataset for training and testing purposes and achieved an accuracy of >91%.

4.2. Crop Identification/Classification

Once a crop is properly cured of all kid of illness and stress, the next critical step for the former is to harvest it at the proper time and market demand. Deep learning can also play an essential role in making a harvesting plan by considering different parameters such as soil type/quality/pH, weather forecast (including temperature, precipitation, humidity, and hours of sunlight), and fertilizers schedule. A research paper [36] is one of this kind. A multi-layer DL architecture was proposed in [37]. It can classify different crop species in a land-covered area by taking satellite imagery from numerous sources. An ensemble of 1-D and 2-D CNNs beat the RF classifier and a chorus of MLPs, facilitating a more accurate classification of summer crops, mainly maize and soybeans. CNN models offer more than 85% classification accuracy for main crops (wheat, corn, sunflower, soybeans, and sugar beets).

The authors in [38] suggested a deep residual CNN (ResNet-18) for weed and crop detection using unmanned aerial vehicle (UAV) photos. The goal was to obtain appropriate performance on an embedded device while retaining the same ResNet-18 model features as the basis for quick UAV mapping. This model enabled the detection and mapping of weeds during UAV flight operations and attained an overall accuracy of 94% [38].

In [39], the authors provided a deep learning classification system for various plants using the Seed-lings dataset, which contains photos of approximately 960 different plants from 12 species at various stages of growth. Three pre-trained models, InceptionV3, VGG16, and Xceptionare were used for the said purpose, but Xception was proven to be the best classifier with an accuracy score of 86.21%.

A prototype for the CNN model was developed in a study [40] to classify different flowers. It used the transfer learning technique, VGG16, MobileNet2, and Resnet50 architectures to classify publicly available flower datasets, and it produced good results and acceptable accuracy. A hybrid MLR-ANN model for effective agricultural yield forecasting was proposed in [41]. It takes input from MLR intercept and coefficients as weights and bias. A feed-forward artificial neural network with a backpropagation training technique estimates the yield of rice crops. The obtained results showed that the hybrid MLR-ANN model outperforms the traditional models in terms of accuracy.

Another deep kind of learning algorithm for classifying plant images to identify plant species based on leaf photos was presented in [42]. CNN and transfer learning both were used as classification techniques. The experimental findings demonstrated that the suggested model effectively extracted and classified characteristics from images. The article referenced [43,44] presented EVI time series to categorize summertime crops using deep neural networks. Two new DL models were developed called Landsat enhanced vegetation index (EVI) time series and long short-term memory (LSTM). Three gradients boosting machines were used as a classifier, including random forest (RF), XGBoost, and support vector machine (SVM). This model claimed to outclass performance in terms of overall accuracy and ability to identify different crop kinds.

A study [45] developed a novel crop-classification method by combining optimal feature selection and the hybrid CNN-RF networks using multi-temporal Sentinel-2 images to classify summer crops. In this study, optimal features were selected using the OFSM model, and both temporal and spatial dimensions were used to get satisfactory classification results in terms of the overall accuracy up to 94.27%.

Another interesting paper [46] developed a deep neural network using the R-CNN concept and was able to identify the fruit type and can classify healthy and unhealthy fruits. The model achieved the optimum result with a grading accuracy of over 99% and 97.86% using CNN and R-CNN methods.

In [47], the faster region-based convolutional neural network (FRCNN) framework was designed to produce a plant detection model and estimate plant densities across a UAV orthomosaic. The results show that accurate two-dimensional maps of plant density can be constructed from UAV imagery highly correlated to essential yield components.

4.3. Identification of Weeds

Identifying all the weeds on a farm is difficult and typically unnecessary. However, accurately recognizing enormous weeds can be a critical first step in effective control. At certain phases of growth, different weed species may appear remarkably similar. Still, they differ considerably in their life cycle, mode of reproduction, effects on plants, and responsiveness to control tactics. In [48], an RGB + NIR camera created a CNN-based classification system to detect and distinguish sugar beet plants from weeds over natural fields using an RGB + NIR camera. The system gave good accuracy in seeing sugar beet plants among the weeds.

The work [49] proposes a classification vision system to classify individual plants from multi-plant images captured in natural corn field environments. Therefore, a dataset of 15,240 images that contains nine plant species, grouped into the classes Crop, NLW, and BLW, was generated. Images were captured under these natural cornfield environments, and plants were of different growth stages. A classical approach to CNN carried out the classification of the plants in the dataset.

4.4. Identification of Water Stress

Agricultural production is heavily dependent on water and is also increasingly exposed to water risks. Furthermore, it is the most water-consuming sector, and a significant water polluter as spraying pesticides and applying fertilizers can pollute both underground and surface water resources. Therefore, improving water management in agriculture is essential for ensuring the agricultural sectors are sustainable and productive. In this regard, article [6] proposed a convolutional neural networks model to identify the water-stressed and typical areas in the maize crop field. The performance of the proposed framework has been compared with ResNet50, VGG-19, and Inception-v3, and the results show that the proposed model gave better output with an accuracy of 93%. While paper [50] developed and tested a novel deep learning-based pipeline model for detecting phenotyping plant water stress areas using pictures of chickpea plant shoots.

In [51], a deep learning technique was proposed to recognize water requirements from aerial pictures of irrigation systems. This automatic detection could aid in the management of the irrigation system, which reduces the maintenance time and expense of the system. Using the Mask R-CNN neural network, the initial results suggested that it is possible to recognize water from images taken by a UAV. The goal was to find and avoid malfunctioning irrigation that could cause under or over-watering by the proper implementation of irrigation plans.

4.5. Weather Forecasting

Weather information is becoming increasingly crucial in the emerging agriculture sector, emphasizing accuracy and control while cultivating crops. The use of information technology, which includes weather forecasts and other features such as satellite and aerial imaging, GPS guidance, sensors, drones, variable fertilizer application, and plant health indicators, is a crucial component of this technique.

Authors [52,53] developed LSTM deep learning models to predict frost in plants by measuring low temperatures. Despite the high computational cost of LSTM models, they provided excellent time-series prediction results to find/expect ice in the plants.

4.6. Fruit Counting

The difficulty of identifying and counting the fruits on trees is crucial in crop yield estimation in agriculture. Manual counting is time-consuming and labor-intensive. The automated crop counting approach can help project yields and organize harvesting plans to increase productivity and profit margin. In [54], a simulated model of a deep convolutional neural network for yield estimation is developed and tested to know the exact number of fruits. It used a modified version of Inception-ResNet architecture, and experimental results showed an average test accuracy of 91%. A comparison of different research studies in terms of the study area, experiment conducted, the method used, and results achieved are shown in Table 1.

Table 1. Applications of deep learning in agriculture.

Ref	Agriculture Area	Problem Description	Dataset	DL Model	Framework	Data Preprocessing	Data Augmentation	Results
[16]	Identification/classification of plant disease	Detection and classification of banana diseases	(Public dataset). Dataset of 3700 images of banana diseases obtained from the PlantVillage dataset	CNN (LeNet architecture)	Deep learning4j	Resized to 60 × 60 pix., converted to grayscale	N/A	F1-scor 0.968
[17]	Identification/classification of plant disease	Classifying and detecting plant diseases from leaf images	(Public dataset). Image of the plants, 87,000 images of healthy and diseased crop leaves from Kaggle	Alex Net	Developed by the authors	N/A	Applied data augmentation techniques	N/A
[18]	Identification/classification of plant disease	Classify the diseases of sunflower leaf	Data collected by the authors using Google Images	Hybrid model Vgg16 and MoileNet	Keras	Converted the images of size 224 × 224 × 3 into an array	Used ImageDataGenerator class	Accuracy 89.2%
[19]	Identification/classification of plant disease	Pest and disease detection in rice crops	- Artificial rice leaf images were obtained through Kaggle and comprised a total of 3355 images - Real Data 200 images were collected from rice fields in Gujranwala, Pakistan	Vgg16 Vgg19 ResNet50 ResNet50V2 ResNet101V2	Keras	Leaf segmentation, background, shadow removal, intensity scaling, and all images were resized to 225 × 225 for uniformity	Data augmentation	• Artificial dataset, accuracy 75.0% • Real dataset accuracy 86.799%
[20]	Identification/classification of plant disease	Plant leaf disease diagnosis process	Collected more than labeled 96k images of healthy and infected plant leaves	CNN	Keras TensorFlow	Altered the contrast of image colors, added Gaussian noise, and used image desaturation.	Geometric transformations	Accuracy 94%
[21]	Identification/classification of plant disease	Prediction of diseases of crops	(Public dataset). Plant Village Dataset contains 54,306 images of leaves and can identify 38 different diseases	DNN	TensorFlow PyTorch,	N/A	N/A	Accuracy 99.24
[22]	Identification/classification of plant disease	Classification and identification of plant diseases	A dataset containing 30,880 training images and 2589 validation images was downloaded from the internet	CNN	Developed by the author	All the images are cropped manually, A square is made around the leaves, and Images are resized to 256 × 256	Affine transformations	Average precision of 96.3%.
[23]	Identification/classification of plant disease	Classification of plant's health	1918 pictures	CNN	Developed by the author	Resized to 224 × 224 and converted to RGB	1918 pictures were obtained and were augmented to 4588 images	Accuracy of 99.58%
[24]	Identification/classification of plant disease	Detection and classification of plant diseases	500 images of 30 different native types of plants of Tamil Nadu	SVM	Developed by the author	Resized to 32 × 32 pixels are converted to HSI format.	N/A	Accuracy 94%
[25]	Identification/classification of plant disease	Detection of the health and several unhealthy tomato leaf images	18,161 tomato leaf images frthe om PlantVillage dataset	EfficientNet-B7 EfficientNet-B4	PyTorch	Resized to 224 × 224	rotation, scaling, and translation	Accuracy 99.89%

Table 1. *Cont.*

Ref	Agriculture Area	Problem Description	Dataset	DL Model	Framework	Data Preprocessing	Data Augmentation	Results
[26]	Identification/classification of plant disease	Classification of tomato plant diseases	PlantVillage dataset	Random Forest	Developed by the author	Image resizing using cubic interpolation and adjusting colors	N/A	Accuracy 97%
[27]	Identification/classification of plant disease	Detection of tomato plant diseases	PlantVillage dataset	ResNet-50+SeNet	PyTorch	N/A	Spin, Zoom, Add noise, and Color jitter.	Accuracy 96.81%
[28]	Identification/classification of plant disease	Detection of tomato plant diseases	PlantVillage dataset	Lightweight CBAM attention module based ResNet20 (Lw_renet20_cbam)	Keras with TensorFlow	labeling, resizing, and rescaling	Augmentation of the raw images	Accuracy 99.69
[29]	Identification/classification of plant disease	detection of tomato plant diseases	PlantVillage dataset	LeNet VGGNet ResNet50 Xception	Keras with TensorFlow	N/A	Image rotation, patch extraction, and horizontal reflection	Accuracy VGGNet: 99.25%
[30]	Identification/classification of plant disease	Detection of tomato plant diseases	PlantVillage dataset	Hybrid CNN (Hy CNN)	Keras	Resize to 224 × 224 × 3	Rotation, flipping and image brightness	Accuracy 98.7%
[31]	Identification/classification of plant disease	Detection of tomato plant diseases	PlantVillage dataset	Segmentation-based CNN	Developed by the author	resize to 256 × 256	N/A	Accuracy 98.49
[32]	Identification/classification of plant disease	Detection of tomato plant diseases	PlantVillage dataset	CNN model	Developed by the author	resize to 256 × 256	Rotating, flipping, and cropping	Accuracy 91.2%
[33]	Identification/classification of plant disease	Detection of tomato plant diseases	PlantVillage dataset	MobileNet Resnet50 Xception Densenet121 Xception ShuffleNet	-	Resize to 224 × 224 × 4	rotating, flipping, bluer, relight and cropping	Accuracy 97.10%
[34]	Identification/classification of plant disease	Detection of tomato plant diseases	Tomato leaf diseases dataset in AI CHALLENGER	Restructured residual dense network	Developed by the author	N/A	N/A	Accuracy 95%
[35]	Identification/classification of plant disease	Detection of tomato plant diseases	PlantVillage dataset	VGG19 AlexNet	-	Downsized to 225 × 225	N/A	Accuracy 98.9%
[37]	Crop identification/classification	Classification of crops (wheat, maize, sunflower, soybeans, and sugar beet)	19 multi-temporal scenes acquired by Landsat-8 and Sentinel-1A RS satellites from a test site in Ukraine	CNN	Developed by the authors	Calibration, multi-looking, speckle filtering (3 × 3 window with Refined Lee algorithm), terrain correction, segmentation, restoration of missing data	N/A	Accuracy 94.60%
[38]	Crop identification/classification	Classification to differentiate crops, soils, and weeds as well as individual weed species	The dataset used in this study was an independent image set with 16,500 image patches	ResNet-18 DCNN classifier	TensorFlow	N/A	Added, for each image, copies of the image that were rotated by 90,180 and 270 and, additionally, for each rotation angle, copies that were mirrored left to right	Accuracy 94%

Table 1. *Cont.*

Ref	Agriculture Area	Problem Description	Dataset	DL Model	Framework	Data Preprocessing	Data Augmentation	Results
[39]	Crop identification/classification	Classification system of diverse plants in precision agriculture	(Public dataset). Plant Seedlings Dataset contains 4750 images corresponding to 12 species	InceptionV3, VGG16, and Xception	Keras	N/A	N/A	Accuracy 86.21%
[40]	Crop identification/classification	Flower classification	(Public dataset). Kaggle flower dataset that contains 4323 images of flowers, with 224 × 224 input	CNN	TensorFlow Keras	N/A	N/A	Accuracy 91%
[41]	Crop identification/classification	Predicting accurate paddy crop yield	(Public dataset). - Two sets of data collected combined into a single dataset - Annual yield of rice in India FY 1991–2020	ANN	Developed by the authors	Cleaning, normalization and feature selection	N/A	RMSE 0.051
[42]	Crop identification/classification	Plant seedlings classification	(Public dataset). Plant Seedlings Dataset contains 4275 images of 12 species	CNN	Keras	Images were resized to 224 × 224 pixels Data	Flip, rotate, scale, flip scale, and histogram	• Accuracy 0.9754% • F-score 0.9766
[43]	Crop identification/classification	Classification of summer crops	19 images from ETM+ and 18 images from OLI	LSTM + Conv1D	Developed by the author	N/A	N/A	F1 score of 0.73 and accuracy of 85.54%
[44]	Crop identification/classification	Prediction the necessary supplements and minerals that should be provided to the dirt	140 pictures of wilting/wilted grass and normal grass captured by an Edge-smart camera ICAM700	CNN	DeepRes Netetc, AlexNet, DenseNet, GoogleLeNet, CaffeNet, VGGNet	N/A	N/A	Accuracy 90%
[45]	Crop identification/classification	Multi-temporal crop-type classification	Collected by authors	CNN-RF	Developed by the author	N/A	N/A	Accuracy 94.27%
[46]	Crop identification/classification	Fruit quality classification	Collected by authors	R-CNN	-	N/A	N/A	Accuracy 97.86%.
[47]	Crop identification/classification	Plant detection and density variation	Collected by authors	FRCNN	-	N/A	N/A	-
[48]	Identification of weeds	Detecting sugar beet plants and weeds in the field based on image data	1969 RGB+NIR images captured using a JAI camera in nadir view placed on a UAV	CNN	TensorFlow	Separated vegetation/background based on NDVI, binary mask to describe vegetation, blob segmentation, resized to 64 × 64 pix., normalized and centered	64 even rotations	• Dataset A: Precision 97% • Dataset B: Precision 99% (P)
[49]	Identification of weeds	Weed Classification from Natural Corn Field	Collected by authors	CNN	Tensorflow	Resized to 128 × 128 × 3	N/A	Accuracy 97%

Table 1. *Cont.*

Ref	Agriculture Area	Problem Description	Dataset	DL Model	Framework	Data Preprocessing	Data Augmentation	Results
[55]	Identification of weeds	Recognize weeds and identify their growth stages	(Public dataset). The dataset consists of 9649 images for various types of weeds, divided into nine classes	ResNet, MobileNet, Wide ResNet, DenseNet	Pytorch	Image resized to 128 × 128	Augmented data by horizontal and vertical flipping, translation, and rotation	Accuracy 93.45%
[6]	Identification of water	Identification of the water-stressed areas in the crop (maize) field	Collected dataset with 1340 RGB images using DJI Inspire-1 Pro UAV	CNN	Developed by the authors	Segmented images were resized to 1792 × 1792 and divided into an 8 × 8 grid to obtain 224 × 224 image patches of the canopy (leaves)	Added Gaussian noise, contrast, saturation, brightness, and random flips	• Accuracy of train dataset 93% • Precision on test dataset 0.9370 • F1-score on test dataset 0.9403
[50]	Identification of water	Monitoring of stress induced by water deficiency in plants	The authors created a new dataset of two chickpea varieties, JG-62 and Pusa-372, containing 7680 images	CNN-LSTM	TensorFlow and Keras	Gaussian noise	Horizontal flipping, rotation, shear, and translation	• Accuracy 98.52% on JG-62 chickpea plant data • Accuracy 97.78% on Pusa-372 chickpea plant data
[51]	Identification of water	Water spray detection	Created by authors and data acquired using UAV	R-CNN	TensorFlow	N/A	N/A	N/A
[52]	Weather forecasting	Frost prediction in crops by estimating low temperatures	Data time series IoT infrastructure generates 144 rows per day	LSTM	Keras TensorFlow	NA	NA	RMSE 0.8068
[53]	Weather forecasting	The prediction of low temperatures	Real data obtained from an IoT system	LSTM	TensorFlow and Keras	Smoothing mechanism	N/A	R2 0.95
[54]	Fruit counting	Predict the number of tomatoes in the images	24,000 synthetic images produced by the authors	Modified Inception-ResNet CNN	TensorFlow	Blurred synthetic images by a Gaussian filter	Generated synthetic 128 × 128 pix. images to train the network, colored circles to simulate background, and tomato plant/crops	Accuracy 91%

5. Deep Learning Techniques in Agriculture

In Table 1, 40 papers are surveyed and compared, which proposed deep learning methods to solve different agriculture issues. We discussed the problems these papers solved, the dataset used, the deep learning model used, the framework used, the data preprocessing or augmentation used, and the results.

5.1. Area of Agriculture

Most of the collected papers focus on six agriculture areas, as given below. The most notable area was detecting and classifying plant diseases with 20 papers. Other areas include the identification and classification of crops (11 papers), identification of water (3 papers), identification of weeds (3 papers), weather forecasting (2 papers), and counting of fruits (1 paper). It can be observed that most papers address image classification to identify diseases, stress, or water contents. Figure 4 shows the category of the examined papers depending on the different areas of agriculture.

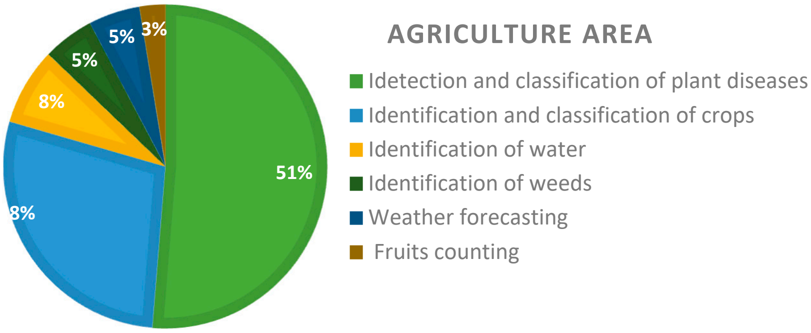

Figure 4. Classification of papers based on different areas of agriculture.

5.2. Datasets Used in Papers

It can be seen that the majority of the research used a dataset containing images to train the models, as such datasets include thousands of photos. Some studies used a public dataset, PlantVillage [56], consisting of 54,303 healthy and unhealthy leaf images divided into 38 categories by species and disease. The majority of them collected and created their own datasets through several methods according to the needs of the research. Papers were concerned with coved land, crop type classification, yield estimation, and weed detection, and utilized a smaller number of images taken by UAV or satellite-based remote-sensing deep learning models. Figure 5 shows the percentage of research studies that used an existing available dataset vs. created and collected their own dataset

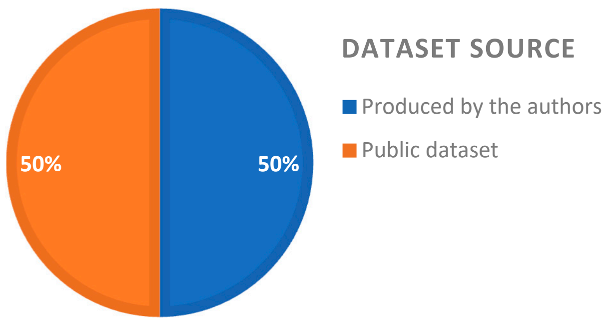

Figure 5. Dataset source.

5.3. Deep Learning Model Used

From the surveyed papers, it can be noted that the majority of them (16 papers) used CNN structures such as AlexNet, VGG16, and Inception-ResNet. Two papers adopted the LSTM model of the RNN algorithm. One paper used deep neural networks (DNN), and another used the artificial neural network (ANN) model. Figure 6 shows the percentage of used deep learning methods in rented research studies.

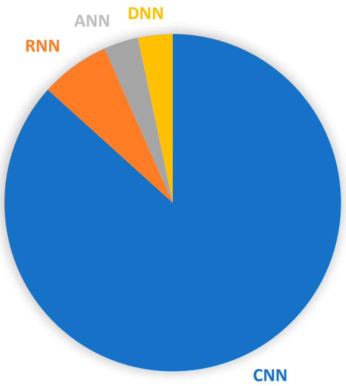

Figure 6. The deep learning model was used.

5.4. Framework Used

Concerning the frameworks used, all the well-known CNN architecture works also used a deep learning framework. The percentage of used frameworks was as follows; Keras (four papers, 32%), TensorFlow (three papers), TensorFlow/Keras (five papers), PyTorch (one paper), TensorFlow/PyTorch (one paper), and Deeplearning4j (one paper). Meanwhile, five papers developed their own framework.

5.5. Data Preprocessing

Data preprocessing is an integral part of deep learning projects, taking up a large part of the entire analytical pipeline [57]. Data preprocessing includes cleaning, normalization, transformation, feature extraction, and selection. In this survey, most research (13 papers) used data preprocessing. Figure 7 shows the percentage of research that used data preprocessing techniques.

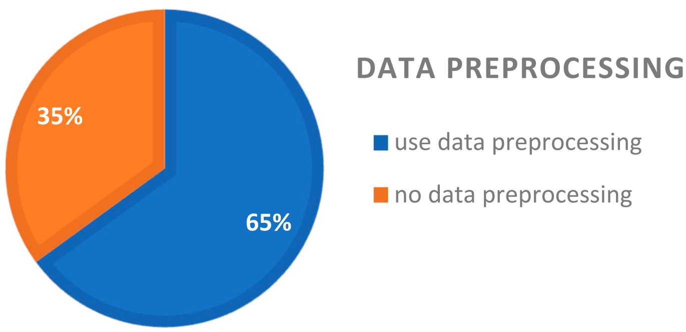

Figure 7. Data preprocessing.

5.6. Data Augmentation

As an effective method for improving the size and quality of training data, data augmentation is critical for successfully applying deep learning models to time-series data [57]. In this survey, several works (20 papers) used data augmentation techniques to enlarge the number of training images artificially. It improves the overall learning procedures and performance while also assisting in generalization purposes by feeding it to the various data models. This incrementing process is essential for the studies depending on small datasets for training the deep learning models. Several data augmentation techniques were applied in the papers surveyed, including scaling, cropping, flipping, padding, rotation, translation, and affine transformation. Figure 8 shows the percentage of other research that used various data augmentation techniques.

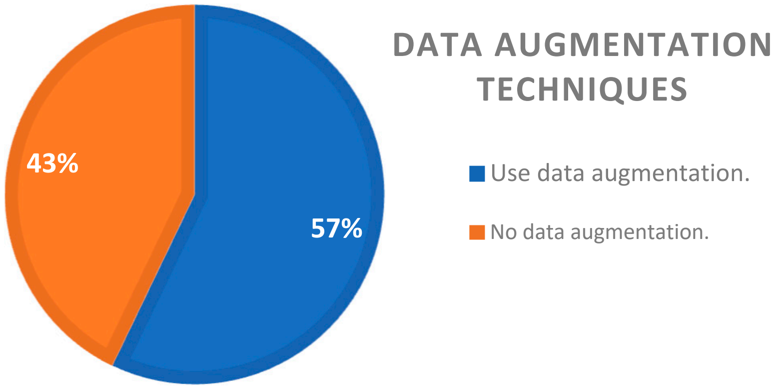

Figure 8. Data augmentation.

5.7. Performance Metrics Used in Results

Several performance metrics were used in the surveyed papers. Table 2 lists these metrics and their definition/ description, and the symbol used to refer to them in this survey.

Table 2. Performance metrics used in related work.

No	Performance Metric	Description
1	Accuracy	This is the % of correct classifications.
2	Precision	Precision is defined as the fraction of relevant examples (true positives) among all of the examples that were predicted to belong to a certain class.
3	F1 score	F-measure provides a single score that balances both the concerns of precision and recall in one number.
4	R^2	The determination coefficient is a statistical measure representing the proportion of the variance for a dependent variable explained by an independent variable.
5	Root Mean Square Error (RMSE)	It is a standard deviation of the errors that occur when a prediction is made on a dataset.

6. Discussion

The agriculture sector needs to be modernized with state-of-the-art technologies to feed the rapidly increasing world population with bio food. Given the increasing environmental problems that negatively affect this sector, it was necessary to move to the use of modern technologies to meet these challenges and issues with high efficiency. Smart agriculture is a vast field that includes a variety of topics such as sensor development, parameter monitoring, data collection, network convergence and maintenance, sensor nodes cluster formation, cluster head selection, data compression, and aggregation, security and integrity, design and development of the expert system, artificial intelligence-based decision making and many more.

The development of artificial intelligence and deep learning in the past two decades has dramatically increased the number of projects in the field of agriculture. The analysis has shown that deep learning techniques offer superior performance in most related work and yield better results than traditional methods in this sector.

Some critical factors that were ignored can exert considerable influence on the decisions made by any AI or deep learning algorithm. We observed that crop, soil, environment, and pest-related information is collected using field sensors before applying a deep learning algorithm to obtain the next course of action; however, other parameters, such as weather forecasts, crop standard procedures, historical crop data, farmer input, and government policies, are not taken into account while decisions are made.

6.1. Advantages and Disadvantages of Deep Learning

The advantage of deep learning is that features are automatically deduced and optimally tuned for the desired outcome. Another benefit is that the same neural network-based approach can be applied to several different applications and data types. Furthermore, the deep learning architecture is flexible and can be adapted to new problems in the future. Deep learning also offers good generalization performance. While it takes more time to train deep learning models than other traditional approaches, its efficiency in testing is quite fast. One of the notable drawbacks of deep learning is that it requires many datasets to give better performance, even if data augmentation techniques are used. Few publicly available datasets exist in agriculture, and researchers need to develop their own sets of images in many cases. This can take many hours or days of work.

6.2. Future of Deep Learning in Agriculture

Agriculture is one of the complex areas of application, as each region has its climatic conditions, nature, and features that differ from the other areas. Therefore, there is an urgent need for technology to distinguish the elements of interest and analyze the collected data. This requires a considerable amount of data to explore, considering changes in real-time. Therefore, in this regard, deep learning is one of the most important technologies that can carry out these functions using appropriate algorithms such as CNN and RNN. When an algorithm is fed with field data, including climate parameters, soil types, weather patterns, and other factors, it builds a probabilistic model before making any decision. Early and accurate identification is essential in tracking different diseases before bearing food or financial losses. After sorting through images of sick plants spanning a decade, this algorithm can determine the type and severity of the disease. The same applies to the course of the weather. The main advantage of a deep learning model is that the software creates the selected feature on its own without provision. Unsupervised learning makes us better equipped and informed to work in the unpredictable and constantly changing real-time environment. It is essential because the significance of the IoT continues to grow, and most of the data generated by humans and machines are unstructured and unclassified. Deep learning outperforms traditional methods, such as ANN, SVM, RF, etc. Automatic feature extraction with deep learning models is more efficient than conventional feature extraction.

7. Proposed System Architecture

The survey concluded that research involved in detecting and classifying plant diseases used convolutional neural network models and object detection techniques to detect and classify plant diseases. Although these models give us high accuracy results, there is a tendency for further improvement. Furthermore, these models are lacking in the early detection of diseases which requires more advancement and hybridization to improve this detection time, accuracy, performance, detection time, and range of conditions. Hence, we proposed a hybrid model (CNN-SVM) for the early detection of plant leaf diseases where many drones captured images will be used as the data set. Then this proposed hybrid model will process the data and generate early decisions. Our model consists of three main parts a CNN model with an attention mechanism applied and an SVM classifier, as shown in Figure 9.

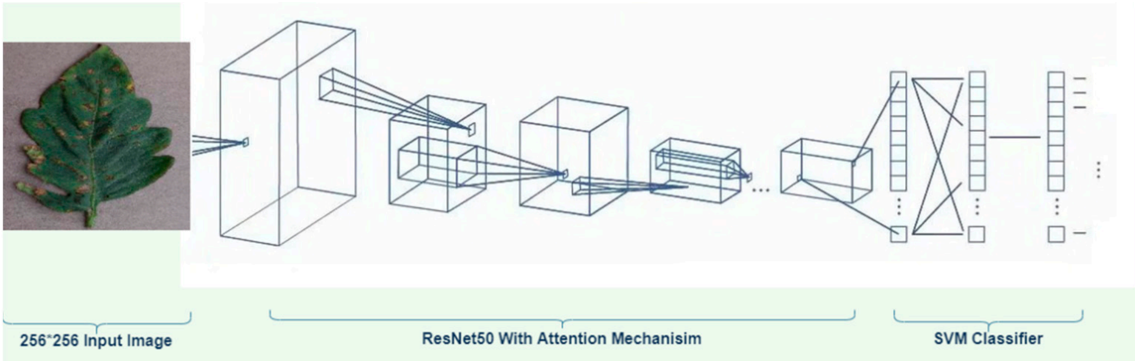

Figure 9. The proposed system.

7.1. The CNN Model

We chose the ResNet50 to be the backbone of our CNN model. The model takes a 256 × 256 image as input and produces a vector of features. The proposed deep learning model consists of four stages in all the surveyed articles, each containing multiple residual blocks to increase the network's performance. They primarily use identity connections to protect the network from vanishing gradient problems. While the ResNet-50 model utilizes batch normalization (BN) layers that help prevent overfitting. Each residual block contains a weight layer followed by a batch normalization layer and a "ReLU" activation layer, then another weight layer followed by another batch normalization layer. Then we are planning to add the input x of the residual block, and then the output of these layers $f(x)$, the final output of the block will come after a "ReLU" activation Layer as per Equation (1).

$$g(x) = f(x) + x \tag{1}$$

7.2. The SVM Classifier

Support Vector Machine (SVM) will be our choice to replace the fully connected layers in the proposed model. The ResNet50 model will be connected with the SVM classifier as the feature vector from the CNN model will be the SVM model's input. As we know, SVM offers efficient results in high dimensional spaces and is effective in cases where the total number of dimensions is larger than the total number of samples. In addition, SVM will be intensively employed in image classification scenarios and will achieve high classification accuracy. SVM constructs a hyperplane in multidimensional space in the proposed system to differentiate varying classes.

7.3. The Residual Attention Network

The residual attention network will be constructed into a stack of multiple attention modules in the proposed system. Each attention module will be divided into the mask and trunk branches. The trunk branch will perform feature processing which any state-of-the-art network structure can adapt. Attention modules will be used to make CNN learn and focus more on the critical information rather than on learning useless background information.

8. Conclusions

In this work, we analyzed recent research efforts related to the use of deep learning techniques in agriculture over the past five years. The published important contributions, as well as the resolved issues, were discussed. During this survey, we considered technical details applied from the datasets used, deep learning models, work environment, data preprocessing, data augmentation techniques, and results presented in the reference articles. Our findings indicate that deep learning performs better than other typical image processing techniques but can improve considerably if specific other parameters are considered. Moreover, deep learning offers a high level of accuracy and outperforms existing, commonly used image processing techniques. In addition, we proposed a hybrid model for the early detection of plant leaf diseases using deep learning techniques.

This work is helpful for researchers trying to experiment with deep learning and apply it for solving various agricultural problems involving classification or prediction and those related to computer vision and image analysis and data analysis in general. Furthermore, this technique has yielded promising results in its application in agriculture, leading to smart and more effective solutions for making agriculture more efficient and sustainable. In the future, we are planning to develop the proposed hybrid deep learning system and evaluate its performance in terms of accuracy.

Author Contributions: Collecting and reading papers, reviewing, summarizing, and paper writing was a collective effort of M.A., A.A. and A.R. While methodology, comparison, discussion, and proposed system are the sections written by M.A. Overall supervision, validation of the design, editing and form result from verification is done by M.A.u. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data presented in this survey is the PlantVillage dataset and it is openly available, reference number [56].

Acknowledgments: The authors would like to acknowledge to Sensor Networks and Cellular Systems (SNCS) Research Center at the University of Tabuk to support this work.

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

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