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Research Article

Rice Disease Detection Using Artificial Intelligence and Machine Learning Techniques to Improvise Agro-Business

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Agro-business is highly dependent on rice quality and its protection from diseases. There are several prerequisites for the procedures and the strategies that are productive and efficient for expanding the harvest yield. The advancement in computer science has supported various domains; agricultural innovation is one of them. The apparatuses which utilize the strategies of advanced artificial intelligence and machine learning have been featured in this paper. These techniques attain abnormally productive outcomes for the recognition of infections engrossing the images of leaves, fields of harvest, or seeds. In this context, this work presents a survey that focuses on accuracy agribusiness for expanding the conception of rice, which is one of the main harvests on the planet. In this paper, the overview and examination of various papers distributed in the most recent eight years with various methodologies identified with crop diseases identification, the health of seedlings, and quality of grain have been introduced. Experiments are performed for knowledge extraction using Web of Science and Scopus databases to analyze research trends in the domain of rice disease identification using artificial intelligence using global analysis, year-wise and country-wise citations, and so on to support various researchers working in this domain.

1. Introduction

Farming has been the bedrock of supportability for the economy of any nation. It has a key impact in long-haul monetary development and auxiliary change. As per Food and Agriculture Organization (FAO) wing of the United Nations, the world population will have increased by 2 billion in 2050. Henceforth, it will be very challenging in the future to use the traditional methods for early identification and diagnosis of crop diseases. Albeit, the fundamental trouble is the preparation of these traditional methods. The other trouble is the time required to complete assessments using traditional methods, which forestalls rapidly dynamic and huge-scope assessment. Rice, after wheat, has been one of the primary crops in the world [1]. For the economy of the underdeveloped nations and farmers, rice has been a

necessary staple food, and the economy and farmers are very much dependent upon the yield of the rice crop [2]. Any crop yield has been highly affected by any type of negative impact (i.e., mechanical harm, wholesome lack, hereditarily clutter, climatic conditions, etc.). Instead of that, the serious issue is ailment caused by microbes and microorganisms. Sicknesses are also a significant reason for return misfortune and lower benefits in rice crop. Various diseases and attacks by pest insects also decrease the crop yield by 8–10 percent yearly [3]. Rice has been a significant food source after wheat and maize throughout the globe. According to FAO, it is developed on the land of 166 Mha year-wise creation rice crop production of 745.17 mt and normal profitability by around five t/ha. It is assessed that by the year 2025, 880 mt of harsh rice should be delivered with an augmentation of about 70% to fulfil the expanding populace prerequisite (as suggested by Lampe in the year of 1995). In India, the complete region of about 42.41 Mha comes under the development of rice crop [4]. During the year 2013, with year-wise creation of 104.40 mt of paddy crop and 3.59 t/ha was the normal efficiency of the crop yield. It has been assessed that constantly in 2021, India is in a position to create hundred and thirteen mt rice to satisfy the expanding food demands of the nation. The increase in rice production must be acquired via developed cultivars and coordinated harvest and irrigation executive's advancements. The significant limitations for the acknowledgment of better result of rice crop are its vulnerability to creepy crawly bugs, maladies, and abiotic stresses. Nonetheless, the infections that have been brought about by various parasites, microscopic organisms, infections, and nematodes are also not kidding dangers to support higher yield solidness [5]. The analysts have observed a decline of 10–15% normal yield of rice in light of 10 significant sicknesses of rice crop. Toward these lines, it has become essential to identify the illnesses of rice ideal for guaranteeing a practical creation of rice. As of now, while a rice illness episode arises at various places, rice ailment experts of various agribusiness research or horticulture authorities see the spot and give guidance to the ranchers. At numerous places, there has not been satisfactory rice ailment pros contrasted with the quantity of ranchers [6]. There has been an incredible requirement for programmed rice illness recognition utilizing effectively accessible gadgets in rustic zones. Recognition of plantation area's creepy-looking vermin is difficult since the bug nuisances are poorly described, they exhibit a wide range of intra-bother size and shade variation, and certain bugs are difficult to distinguish outwardly, despite obvious lateral design [7]. The manual methods employed for the identification of numerous illnesses in rice crops can be highly complex, requiring a high level of efficiency in the identification process [8]. When pest insects are present, the entire process of disease identification becomes considerably more complicated, and the analyst must interpret the process from still photographs. The pest insects' images captured with varied perspectives, jumbled foundations may alter the entire process, such as turn, clamour, and so on. As a result, the insect pest photographs that have been captured will be amazing. As a result, the development of a robotized structure for paddy field creepy beetle trouble detection evidence is enormous. On the programmed differentiating verification of the photos of insect troubles, PC vision approaches are extremely important [9]. Typically, paddy crop producers and agriculturists use personal expertise to physically identify the infection and treat the resulting diseases. When manual experience is employed to distinguish diseases, there is a risk of making mistakes. In traditional tactics, the time complexity is significant, and it is difficult to correctly identify the disease and assess its polluted territory in assisting large areas of farming [10]. The detection of disease and pest insects on a timely basis has proved critical for agricultural output. There is a necessity for innovation for this reason, and by applying it, the challenges can be answered more correctly. There are various automation approaches in agriculture leading to agronomics. Various new techniques have been aiming towards the development of disease and pest detection that help to deepen the quantity and the crops' quality for the farmers and the person doing agriculture [11]. In agriculture, an Artificial Intelligence (AI) technique has a great potential to provide the information regarding the quality of soil, when to sow, where to spray herbicide; it is maximum probability of the pest infestation. AI techniques have been used globally, which help the farmers in improving the efficiency for monitoring of crop health. They can be used for disease management for almost every crop. AI techniques that have been used for creating and developing intelligent machines are used for crop management with higher accuracy than humans can do [12].

Agriculturists have been adopting the techniques of artificial intelligence and machine learning for increasing the efficiency of the crop management, which includes detection and curing the crops from various diseases and pest insects. The intelligent systems have all been set to become most used techniques in the coming days, which respond to the different situations and are based on learning; these techniques increase the efficiency to tackle these types of situations. Machine learning, computer vision, satellite imaging, artificial intelligence, and data analysis are emerging technologies and best environment for the creation of an ecosystem required for smart farming [13]. These technologies have been an addition to achieve high average crop yield and the better price control for farmers. Using machine learning, the only detection and diagnosis of rice diseases and pest insects can be done in three stages, which includes preprocessing and segmentation stages, feature extraction of different diseases or pest insects, and recognition of the type of disease or pest insects as shown in Figure 1. The techniques which have been used for the implementation of recognition steps have high detection and classification accuracy [14].

Different types of machine learning methods/methodologies which can be utilized for identification and detection of rice diseases are as follows.

Integrated Pest Management. The pests are very dangerous for all the commercially groomed agricultural crops and they affect the different stages for identifying rice diseases or pest insects yield as well as the normal

Figure 1: Different stages for identifying rice diseases or pest insects.

growth of the crop. Since the 1960s, Integrated Pest Management (IPM) [15] has become a very dominating paradigm for pest control and has been advertised by researchers, agriculturists, and various agencies globally. Integrated Pest Management requires observing of various species of pests, permitting the improvement of ideal pesticide suggestions that advance ideal monetary, natural and sociological results. Along these lines, the precise acknowledgment and pest quantitation is of much significance for the successful utilization of IPM. Be that as it may, the current observing practices are costly and tedious, as they require IPM experts to physically gather and arrange examples in the field, blocking the expansion of this innovation to areas that do not have this specialized help. Economical techniques are increasingly required, and computerized frameworks dependent on PC vision and AI have been developed as an energizing innovation that can be applied to this issue.

Support Vector Machine. For the problems of classification and the regression problems, the support vector machine has been one of the most popular tools based on machine learning techniques. Based on statistical learning framework or VC theory, SVM is a nonlinear classifier and it can arrange the highlights into 2 classes. By presenting a hyperplane, the component vectors can be isolated into different specified classes [16]. The primary goal of SVM is to accomplish extreme separation between the hyperplane and the class limit to stay away from the process of misclassifying of vectors into different classes. The element vectors that are available at fringe of a class and dependent on the hyperplane separation are chosen and are called a support vector.

Convolutional Neural Network. Artificial Neural Networks with numerous layers are termed as Deep Neural Networks or Deep Learning. It has been explored as one another key resource in recent years and has become quite well recognized in the literary community because of its efficiency to manage with huge amounts of data [17]. The most well-known profound neural network is the Convolutional Neural Networks (CNNs), which takes its name from operation of mathematical dimension from the matrixes termed convolution. Convolutional Neural Network (CNN) has various types of layers; it includes pooling, nonlinearity, and convolutional and fully connected layers. Convolutional Neural Network has pivotal outcomes over previous decades in an assortment of fields identified with design acknowledgment, from picture handling to voice acknowledgment [18]. The significant part of CNN is to get theoretical highlights when information proliferates towards the more profound layers. For instance, in picture characterization, the edge may be distinguished in the principal layers, and afterward the less difficult shapes in the subsequent layers, and afterward the more elevated level highlights.

The following are various types of CNNs, which can be used for the purpose of image classification:

AlexNet is a variety of deep convolutional neural network (DCN-Network), which was initially intended to distinguish almost one million high-goal images into 1000 distinct classes in the challenge of 2010 (ILSVR challenge). It almost has an aggregate of 8 hidden layers of neurons, which contain 650,000 of neurons [19]. Deep-CNN is a highlighted technique for learning visual highlights in depth. It includes a layer-oriented convolutional-deconvolutional algorithm with Symmetric Skip Connections (SSC) between rotating convolutional-deconvolutional layers for deep learning of visual peaks. The deep CNN is made up of continuous linear and nonlinear capacity. Convolution tasks directly express linear functions, while nonlinear functions convey unanticipated actions [20]. The convolution layer recognizes the adjacent properties of paddy crop images and begins sophisticated component depictions of paddy diseases. Back-propagation neural network follows a technique of neural network that is multiple-layer and feedforward neural network that has at least 3 layers, namely, hidden, input, and the output layers [21]. The steady change of the loads makes the right pace of the system reaction to the info mode. Local Binary Pattern Histograms (LBPH) is a basic and proficient classifier, which has been utilized for surface separation and picture highlight extraction and has demonstrated to be vigorous concerning the varieties in revolution and enlightenment. The classifier names the pixels by using thresholding of the 3-by-3 neighbours of every pixel with the middle an incentive to deliver a parallel fix. The LBP Histograms utilize the marks of the histograms as a descriptor to the surface of the fix. Afterwards, the classifier is stretched out to an adjacent neighbourhood of various sizes, and a Circular-LBP term has been coined for it [22].

k-nearest neighbor (kNN) algorithm stores all the cases that are available and based on a similarity measure and classifies the new one. k-nearest neighbor strategy broadly utilizes the use of data mining and AI because of its basic usage and recognized execution. In any case, setting all test information with a similar k value in the past kNN strategies has been demonstrated to make these techniques unreasonable in genuine applications [23]. The kNN classifier has been very efficient with execution on information with a huge model size. The presentation of the kNN grouping can be influenced by certain issues, for example, the choice of the k esteem, the determination of separation measures, and so on. As of late, numerous methods have been created to conquer these issues.

The idea behind the Residual Neural Network (RNN) has been taken from ANN, which has been developed dependent on the cells placed on the pyramids of the cortex of the cerebral accomplished by utilizing skip associations bouncing over the layers of the portion [24]. These ordinarily twofold or triple layers avoid having the middle of non-linearity and normalization of the batches. The skip loads are found out utilizing an additional weight lattice, called the Highway Nets. This network has exceptionally been useful for maintaining a strategic distance from the obstruction of inclinations evaporating with more profound nets.

1.1. Image Segmentation. The process in which division of an image is processed into multiple parts called Segmentation of an Image [25], by which relevant information and objects can be identified. The different ways present to perform the process of image segmentation are as follows:

(i) Threshholding method (e.g., the method suggested by Otsu)

(ii) Segmentation depending on the image colors (e.g., k-means of clustering)

(iii) Transformation method (e.g., segmentation using watershed technique)

(iv) Based on the image texture, such as texture filters

Segmentation of computerized picture is essential to work with it. Various kinds of data that can be acquired from the picture if it is segmented in an appropriate manner [26].

Clustering applies to elevated levels depicted on the content of the image captured. The objective of the clustering task is to discover a planning of the chronicle pictures into classes (clusters) with the good goal that the arrangement of classes gives basically a similar data about the picture file as the whole picture set assortment. The created classes hence can give a succinct rundown and perception of the picture content that can be utilized for various assignments identified with picture database the executives. Image clustering empowers the usage of productive recovery calculations and makes use of interface to the database easier [27].

An approach to use the techniques of the image clustering involves the addressing of the almost three important issues, which are as follows:

(i) Features of an image (i.e., different ways of how the image is represented)

(ii) Feature data for organization (i.e., ways of organizing the data)

(iii) Classifier (i.e., how an image to a certain cluster has been classified)

1.2. k-Means Clustering Algorithm. This algorithm solves the problem of image clustering [28]. For its implementation, first, the number of clusters is decided and the following steps are performed afterwards:

(1) Initializing the centre of clusters.

(2) Attributing the fixing data point of the closest cluster.

(3) The data points mean of each cluster is fixed to the position of each cluster.

(4) Continuing with steps 2 and 3 till the procedure converges.

2. Related Work

This part of the article represents a scientific literature to spot the task that is expounded to the utilization of AI, neural networks, and laptop purpose for identifying the rice/paddy illness and tormentor rice insects. The literature is predicated on the methods utilized for the assimilation of the rice sickness mistreatment computer science techniques. Phadikar built up a computerized framework to detect the diseases like leaf brown spot and leaf blast of rice crop consequent to the changes of the morphological study of the plants deliver due to the infections [29]. Classifiers based on Bayes hypothesis and SVMs have been applied to diseased images for characterization and exhibition, which have been analyzed. The distribution of radial of dusk from the middle to the spot at the boundary pictures has been utilized as highlights to arrange the sicknesses by SVM and Bayes' classifier. Almost, 500 samples of all information classes have been used to test the framework. At the primary level of characterization (e.g., for a disinfected leaf or a diseased leaf), it has been discovered that rate of detection is around 92% for the disinfected leaf, 96% for leaf's with brown spot and 84% for the leaf's with blast. In the presented work, a framework has been produced for recognizing two distinct sorts of diseases in rice crop. In the primary stage, grouping of the disinfected and the diseased leaves has been done, which depends on the quantity of peaks in the histogram. Disarrangement may happen because of shadow impact and shading twisting of maturing leaves. In the subsequent level, Bayes' classifier and SVM have been applied to categorize the diseases of the leaves. The presented framework utilizes around thousand test spot pictures of infected leaves of the rice crop gathered from the field, giving accuracy of 79% for Bayes and 68% for SVM classifier oriented framework separately [30].

Pinki et al. suggested a methodology for identifying the rice crop disease at an exceptionally primary stage and the farmers and agriculturists can take advantage of the same in order to minimize the crop yield loss. Firstly, paddy leaf image is taken and afterwards handled for improvement [31]. Then, the captured image is transformed from RGB color image to gray image and by utilizing MATLAB functions. The resultants obtained can be used to distinguish the disease from grouping of illnesses and detection of the infections. Afterwards for the sake of finalizing the crop disease recognizable proof and stage identification, an expert consultation is done. For testing purposes, different samples of leaves have been taken. In this work, the author has suggested another histogram-based idea of recognizing diseased paddy leaves. Using histogram, between the impact factors among the first paddy leaf and the illnesses

influencing paddy leaf, the extraction distinction between these two was done. They have taken 3 paddy diseases of leaf (i.e., blast, bacterial leaf blight, and rice Tungro infection). More test images have been delivered, and the probability of recognizing different mistakes during the recreation has increased automatically. The suggested methodology shows a solid and methodical method of surveying diseases in rice crop during the initial stages. The consequences of the primer test show better aftereffect of infection extraction. The normal classifier precision estimated for various diseases as referenced is 90% (blast—80%, bacterial leaf blight—92%, and rice Tungro—90%). Nagarajan et al. offered a structure which utilized the bag-of-words approach of features based on gradient, with the images of rice field pests arranged. Twenty different classes' images of the rice crop pest insects were taken from Google Photos and images clicked by the researchers of the Jaffna University, Sri Lanka. The grouping of images was then done using the framework that includes a proof of the presence of symptoms in the areas of portrayal and intrigued of the infected districts as scope-variant feature transform (SIFT) or SURF. Then, codebooks, descriptors were developed that gave AN approach by that a vector of fixed length will be planned in bar graph area, and therefore the multiclass order of the component histograms utilizing support vector machines. Besides, HOG descriptors were applied orderly [32]. The gauge classifier approach of highest neighbor was used and contrasted with SVM-based classifiers. The results obtained showed that descriptor of HOG basically outflank existing close unvaried highlights. MATLAB has been used for the implementation of all experiments on a PC with Intel Core 2 processor (2.4 GHz) and 4 GB RAM. HOG descriptors along with SURF features yielded around 90% precision in arrangement.

Rahman et al. suggested a procedure to deal with recognition of generally occurring illness in rice plant in particular leaf impact utilizing SVM. With the ongoing headway in picture preparation and design acknowledgment strategies, it has been conceivable to build up a self-sufficient framework for disease diagnosis in crops [33]. The article has been divided into five domains, that is, Part I managed image acquisition, Part II image preprocessing, Part III image segmentation, Part IV managed feature determination and feature extraction, Part V depicts SVM classifier utilized for disease arrangement, and Part VI comprised result examination. The image database has been taken from International Rice Research Institute. Segmentation process has been completed utilizing k-means clustering algorithm and the infected bits of leaves are obtained. The surface element vectors that were removed from the fragmented pictures were fed to classifier as input. Islam and Rafiqul work fragmented the picture into three pictures dependent on leaf shading because of sickness. To deal with performance of the image segmentation, a viable way has been used which utilizes algorithms, instruments, and an extensive situation for data analysis, visualization, and algorithm improvement. Among the pictures unaffected, leaf districts and infection influenced areas have been utilized to determine the level of affected pixels. The outcomes acquired from the above activity showed that about 11.23% of the first picture has been infected by infection. The estimation of inspected pixels of the picture has been 100% accurate. By figuring the level of affected pixels, the seriousness of disease can be seen, which prompts taking proper measure for treatment [15]. Chung et al. suggested a strategy to seeds which are three weeks old and contaminated with Bakanae infection. Infected plants can produce void panicles or die, bringing about lost grain yield. The infection happens almost every now and then when infected seeds are utilized. When the seeds are defiled, the microorganism *Fusarium* scatters in the field. In this way, infected plants can be screened at early formative stages. The pictures of contaminated and control seedlings have been gained utilizing flatbed scanners to evaluate their morphological and shading characteristics. Support vector machine classifiers have been produced for recognizing the contaminated and solid seedlings. A hereditary calculation has been utilized for choosing basic characteristics and ideal model boundaries for classifiers of SVM. The approach developed in this work recognized contaminated and solid seedlings with good result of 88% and a +ve predictive value of 92% [10]. Ding and Taylor suggested an automated detection pipeline dependent on deep learning for distinguishing and taking into account the different types of pests in pictures considered in the field traps. The work applied best in classical deep learning methods for bug location and tallying, viably expelling the human from the circle to accomplish a totally automated, ongoing bug checking framework. This technique has been applied to a dataset of commercial codling moth and showed good execution both qualitatively and quantitatively. Contrasted with past endeavors at pest identification, this methodology utilized no vermin explicit designing, which empowers it to adjust to different species and situation with negligible human exertion. As compared with the past research work, the suggested technique depends more on information and less on human information when applied on codling moth dataset [11].

Prajapati et al. produce a model framework for finding and grouping of rice crop diseases based on the pictures of infected rice plants. This article endeavors for considering the ideas of Machine Learning and Image Processing to take care of the issue of the auto detection and grouping of maladies in the rice crop field, which is one of the significant nourishments of India. Ailments in any plant have been brought about by microbes, organisms, and infection. The presented framework has been created after nitty-gritty test investigation of different methods utilized in picture handling tasks. The work considered three rice plant sicknesses (i.e., bacterial leaf blight, brown spot, and leaf smut). The different highlights have been separated under three classes (i.e., shading, shape, and surface). For multiclass characterization, Support Vector Machine (SVM) has been used and 93.3% precision and 73.3% exactness have been accomplished on preparing dataset and the test dataset, respectively. After performing 5- and 10-fold cross-validation, the accuracy accomplished is 83.80% and 88.57%, separately [34].

Rautaray et al. suggested a framework, which has been automated in nature for finding three regular diseases of rice leaves: bacterial light blight, leaf blast, and brown spot. *k*-means clustering algorithm has been utilized for the detection of the diseases from the affected part from paddy leaf picture. To arrange these diseases, test substance such as upper part of leaves, shading in leaves, and shapes of leaves have been utilized for highlighting process. The diseases exist in the leaves of rice have been sorted by the Support Vector Machine classifier. The procedure for curing the disease has been suggested, which helps individuals and agriculturists associated with horticulture to take necessary actions against the infections [35]. The presented framework has two stages (i.e., the training stage (some sickness-influenced paddy leaf pictures have been utilized to prepare the SVM) and the testing phase (test pictures are caught by camera from the paddy field)). The image has been handled and highlights of this image have been separated utilizing similar procedures of the preparation stage. At that point, a component vector is constructed and forwarded to the classifier (for perceiving the paddy leaf ailments). This suggested framework has focused on perceiving the paddy leaf infections, which helps the ranchers for a legitimate estimation and expands the creation of paddy. The suggested framework showed an outcome with a precision of 92.06% as compared to current techniques.

Sarowa et al. have suggested a three-layered strategy to identify WBPH (white-backed planthoppers) and their impressible stages utilizing image processing. In the first 2 layers, an AdaBoost classifier (prepared on a histogram of arranged gradient highlights) has been used, a Support Vector Machine classifier (prepared on LBPH), and Gabor to recognize white-backed plant hoppers and evacuate the polluting influences. The accomplished work has an identification pace of around 86% and a bogus location pace of 10%. In the 3rd recognition layer, a classifier of Support Vector Machine has been utilized to distinguish the distinctive formative phases of the white-backed planthoppers. It has accomplished a recognizable proof pace of 73%, a bogus ID pace of 23%, and a bogus location rate of 6% for the pictures without planthoppers. The presented novel three-layer location strategy roughly took 8 s to distinguish and recognize the planthoppers in a single rice picture. The technique was plausible and successful for the identification of different impressible phases on rice plants planthoppers [36].

Rajmohan et al. introduced a sensor-based mobile app system for facilitating business of agriculture, which fits agriculturists with significant data about the paddy yield and its condition [37]. The suggested sensor-based Smart Paddy Pest Management model is fused with a versatile application. The method of the suggested system includes two modules, namely,

(i) Identifying disease affecting the crop

(ii) Management of disease, which includes remedial measure for the disease

The identification of the disease is related to recognizing what sort of contamination has happened in the paddy crop. Malady management is used to decide the aftereffect of infection recognizable proof, which is hinted to the rancher through portable application. Among the collected 200 diseases pictures with diseased leaves, the number of genuinely recognized images that has symptoms for blast disease, brown spot disease, bacterial leaf blight (BLB), sheath blight, false smut, root knot nematode, and white tip infected distinguished was 175 under different types of classifications. The accuracy rate considered paddy crop disease classifier images is 87%. The suggested system includes Deep-CNN. Also, SVM classifier has been contrasted and the past methodology which was actualized by joining *k*-means and fuzzy logic classifier and KNN and SVM classifier. It is discovered that the suggested approach has proven to accomplish enhanced arrangement. Ramesh and Vydeki use the process of computerized image rice infections detection process for brisk determination of the illness. The authors carefully caught illness contaminated and sanitized plant pictures saved in the database, which conveyed unique component descriptor information about the color, texture, and spatial frequency information. In this exploration, five classes of contaminated and one classification of cleaned pictures put away saved in the database were carefully processed. The pictures were converted to RGB shading space and edited and resized using prepreparing steps. The two-way ANOVA investigation was considered in wavelet highlights to assess *F*-ratio [38].

Sethy et al. presented an overview of the identification and characterization of sickness in rice plants utilizing the pictures of infected rice plants. The diseases targeted in this work were leaf smut, bacterial leaf blight, and brown spot. The UCI Machine Learning Repository has been utilized for procuring the Rice Leaf Disease Dataset. To characterize the obtained pictures into a wanted disease class, RNN has been utilized, which has been seen as a fast, profoundly proficient procedure and produced desired results over the CNN and different classifiers. The efficiency of the suggested work has been proved with an accuracy of around 95.8% on the used datasets [39].

Shrivastava et al. have suggested a video discovery framework for identification of plant sickness and bugs. And to fabricate a continuous yield sicknesses and irritations video identification framework later on, a deep learning-oriented detection of videos design with a characteristic backbone has been suggested by for distinguishing plant sicknesses and bugs in video recordings. In the suggested work, the video was changed into still frame, and the video frame is sent to the still-picture detector for detection, and in the end, it combines the frames into video. In the still-picture finder, the authors utilized faster-RCNN as the structure. They utilized picture preparing models to recognize moderately foggy recordings. Furthermore, a lot of video-put together assessment measurements based with respect to an AI classifier were suggested, which mirrored the nature of video discovery successfully in the trials. The tests

Table 1: Comparative analysis of techniques used for target disease detection.

S. no.	Year	Technique used for disease detection	Target	Used for detection of	Accuracy percentage
1	2012	SVM and Bayes' classifier	Leaves	2 diseases	Baye's—79.50%; SVM—68.10%
2	2012	Image processing and MATLAB	Leaves	3 diseases	Blast—87% Bacterial leaf blight—92% Rice Tungro—90%
3	2014	SIFT, SURF, HOG, and SVM	Insect pests	20 types of insect pests	90% accuracy in classification
4	2015	SVM	Leaves	1 disease	Support vector machine enables categorizing the diseases with an accuracy of 82%
5	2015	Segmentation of images and *k*-means clustering method	Leaves	1 disease	Counting pixels calculation of the image is 100% accurate
6	2016	SVM	Seedlings	1 disease	Accuracy of 88% and a positive predictive score of around 92% are achieved for differentiating the healthy and infected seeds
7	2016	CNN	Insect pests	The approach used in this study is not pest specific, which makes it possible to adapt this approach for different species and environments	The suggested method relies on data rather than human knowledge as suggested in previous works
8	2016	Deep convolutional neural network learning	Pests	12 species of pests	Mean accuracy precision of about 0.951, which shows a significant improvement over previous method
9	2017	SVM	Leaves	Three diseases	Training dataset achieves an accuracy of 93.33% and test dataset achieves accuracy of 73.33%
10	2017	SVM	Leaves	Three diseases	Overall accuracy—92.06% 90.9% for brown spot Around 94% for leaf blast 85% for bacterial leaf blight
11	2017	AdaBoost classifier and SVM	Paddy fields	Density of white-backed planthoppers	Rate of identification 85.6% and rate of false detection 10.2%
12	2017	Image processing and ANN techniques	Seedlings	Germination prediction	Precision score was 7.66% false accepted and 5.42% false rejected
13	2017	kNN classifier	Leaves	2 diseases	For geometrical features, kNN classifier has given 76.59% of accuracy
14	2017	*k*-means clustering	Leaves	2 diseases	Suggested approach is able to find the healthy leaf area and injured disease area accurately
15	2018	AlexNet	Leaves	3 diseases	Produced the result of 91.23% accuracy
16	2018	Deep-CNN and SVM classifier	Leaves	7 diseases	Found success rate for considered paddy crop disease affected images is 87.50%
17	2018	Fuzzy logic and machine vision tool for estimating the severity of leaf disease and SVM	Leaves	4 diseases	Suggested method estimated to give up to about 86.35% of accuracy
18	2018	Principal component analysis and back-propagation neural network (PCA-BP)	Harvested lesion	1 disease	Average recognition rate of rice blast is 95.83%
19	2019	SVM and CNN	Leaves	4 diseases	Method can classify rice diseases with accuracy of 91.37%
20	2019	Stacked-CNN and VGG-16	Leaves	9 diseases	An accuracy of 99.53% on test set using the CNN architecture, VGG-16
21	2019	CNN, SVM, LBPH, and Haar-WT	Leaves	1 disease	95.83%—CNN 95%—CNN + SVM 82%—LBPH + SVM 83%—Haar-WT + SVM
22	2019	Classification and regression tree, fuzzy inference system, multilayer perceptron neural network	Leaves	5 diseases	Model achieves an accuracy of 97.1% with training and 95.47% with testing

Table 1: Continued.

S. no.	Year	Technique used for disease detection	Target	Used for detection of	Accuracy percentage
23	2019	DNN with JAYA optimization algorithm	Leaves	4 diseases	98.9%—blast affected 95.78%—bacterial blight 92%—sheath rot 94%—brown spot
24	2019	Machine learning algorithms containing that of kNN, naive Bayes and logistic regression, decision tree	Leaves	3 diseases	Achieved an accuracy of over 97.91% with decision tree algorithm, after 10-fold cross-validation
25	2019	kNN, BPNN, naive Bayes, and SVM	Leaves	5 diseases	An accuracy of 98.63% is achieved by the SVM, which is better when compared to other classifiers
26	2020	RNN	Leaves	3 diseases	An accuracy of 95.83% is achieved by the method
27	2020	RCNN and image detectors	Leaves	Diseases and pests	The experiments show that the method used is more suitable than ResNet-50, VGG-16, YOLOv3, and ResNet-101 backbone system
28	2020	CNN	Leaves	3 diseases	94% accuracy and categorization of various kinds of rice with disease leaves with 78.44% accuracy
29	2020	VGG-16 architecture	Leaves	6 diseases	Using learning method of transfer achieves 90% accuracy

demonstrated that the framework with the custom backbone was increasingly appropriate for identification of the undeveloped rice recordings [40].

The automatic framework can perform sickness acknowledgment at least expense and mistake without the agriculturist master's understanding. It is hard to physically recognize fitting properties for recognizing various types of yield maladies by utilizing picture handling and AI strategies. In this investigation, Shrivastava et al. have built up a CNN structure, a profound learning method for consequently grouping three sorts of rice leaf sicknesses, for example, bacterial blight, blast, and brown mark. In the principal stage, the created frame work recognized solid and ailing leaves from a lot of 1500 rice leaves. In the subsequent stage, the 3 sorts of illnesses have been classified from a dataset including 500 pictures of each or the three sorts or sick rice leaves [40]. The CNN model consequently took in required properties from crude pictures to separate the sound and sick rice leaves with 94% exactness and afterward classified various types of ailing rice leaves with 78.44% precision. Comparative analysis of techniques used for target disease detection is shown in Table 1.

3. Experimental Analysis for Knowledge Extraction of Rice Disease Detection in Artificial Intelligence

Experiments were performed for knowledge extraction using Scopus and Web of Science Database, using Rice, Disease Detection and Artificial Intelligence as keywords, to understand the research trends in this domain and work done by various authors.

3.1. Cooccurrence Analysis of Artificial Intelligence and Rice Disease Detection. Figure 2 describes the cooccurrence analysis of AI and rice disease detection, using Scopus database for experiment. Big data, Internet of things, Genetic Algorithms, and so on are various domains related to Artificial Intelligence and disease classification, rice diseases, and image segmentation are related domains of rice disease detection. The cooccurrence analysis shows that AI has wide application in agriculture and cultivation, especially with rice disease detection. The blue color coding states the domain where AI and rice plants have cooccurrences; red color represents the domain of rice diseases and green depicts the applied AI domains. Hence, the Scopus analysis depicts the correlation of rice diseases with artificial intelligence.

3.2. Global Analysis and Scopus Document Citation. Figure 3 depicts the number of Scopus document citations by various authors. There are limited authors working in AI along with agricultural domain like rice disease detection, and most authors are from recent past (i.e., 2016 and 2017). Table 1 shows a global analysis of rice disease detection using AI, where most work is being done in India, being formerly an agricultural land. China have 2nd list of documents but has more citations than Indian documents. Table 2 shows the top 19 countries working in this domain, with US being on number 4 and Ukraine at the end.

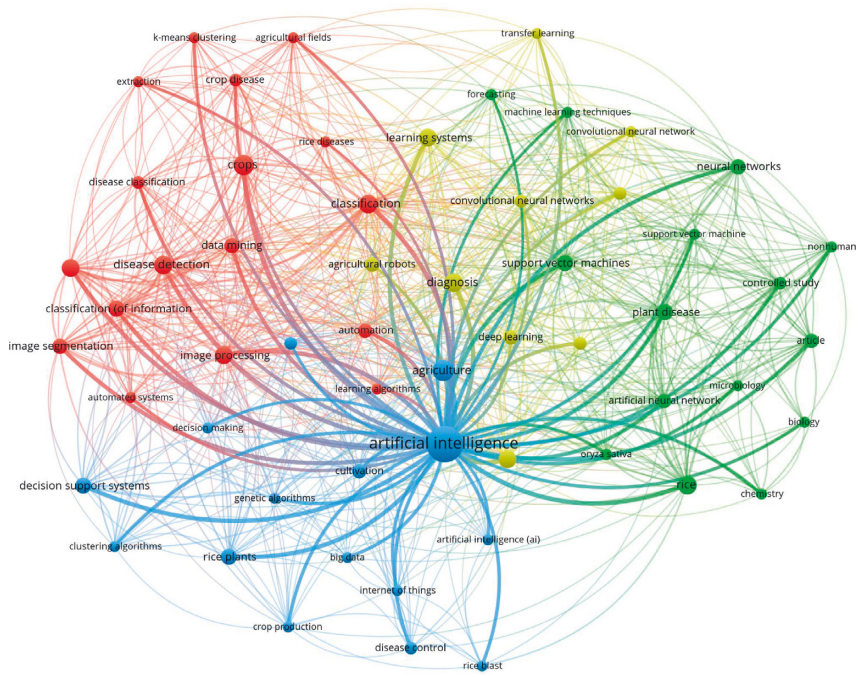

Figure 2: Cooccurrence analysis.

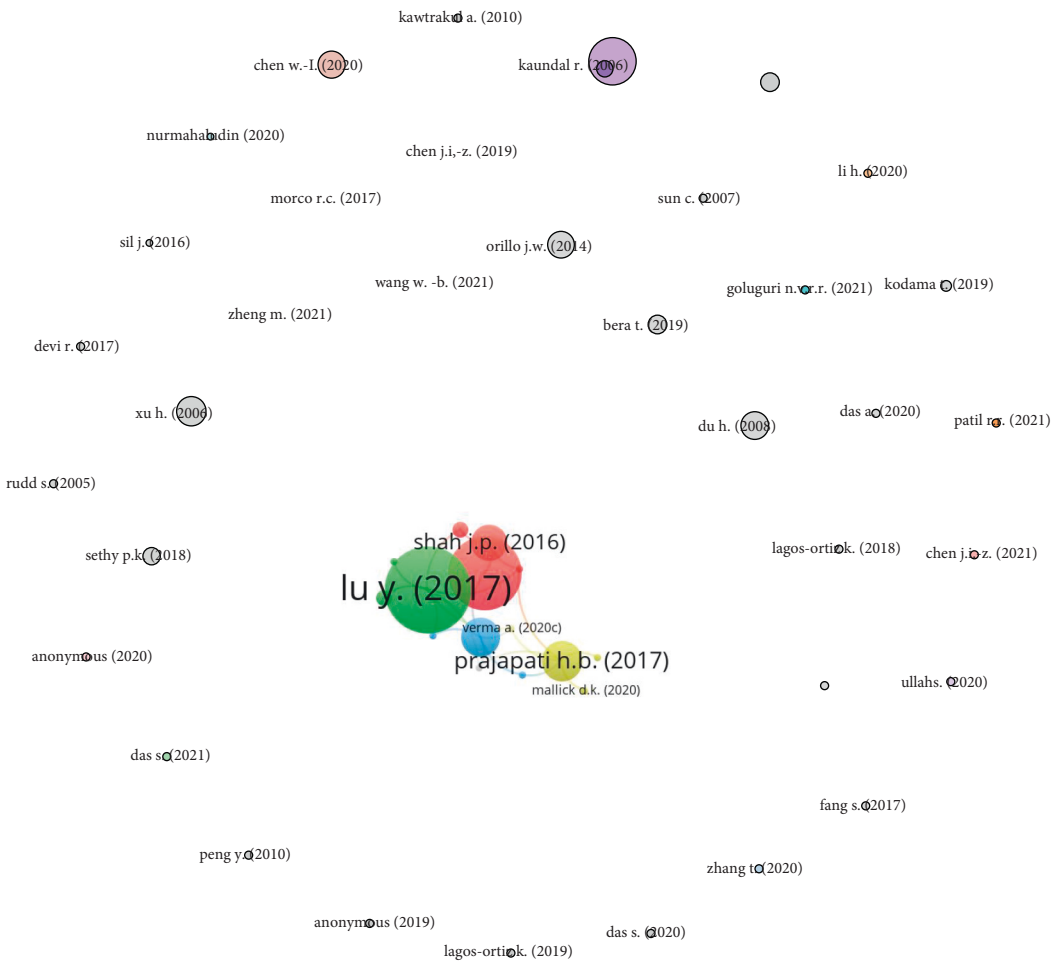

Figure 3: Scopus document citation.

Table 2: Country-wise document citations.

Sr. no.	Country	Documents	Citations
1	India	19	266
2	China	9	345
3	Taiwan	4	98
4	United States	4	79
5	Bangladesh	2	11
6	Ecuador	2	7
7	Indonesia	2	1
8	Philippines	2	40
9	Saudi Arabia	2	299
10	Spain	2	7
11	Thailand	2	16
12	Brazil	1	217
13	Finland	1	2
14	France	1	0
15	Germany	1	2

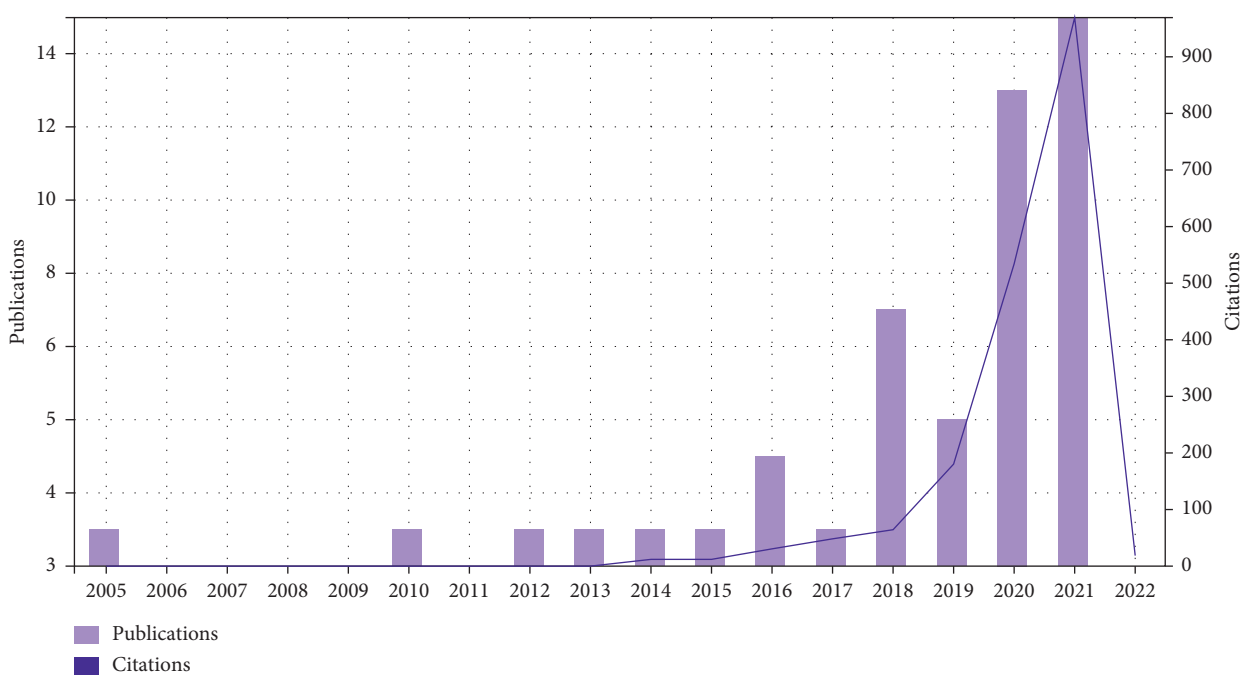

Figure 4: Year-wise analysis (source: Web of Science database).

3.3. Year-Wise Analysis Using Web of Science Database. Experiment was conducted for year-wise analysis of publications and citations for rice disease detection using AI (see Figure 4). It was found that the research in this area started in 2005, with gradually taking pace in 2010. Since 2012, there has been exponential rise in the work performed by various researchers especially from 2019 to 2021. With the experiment conducted, it can be safely predicted that there would

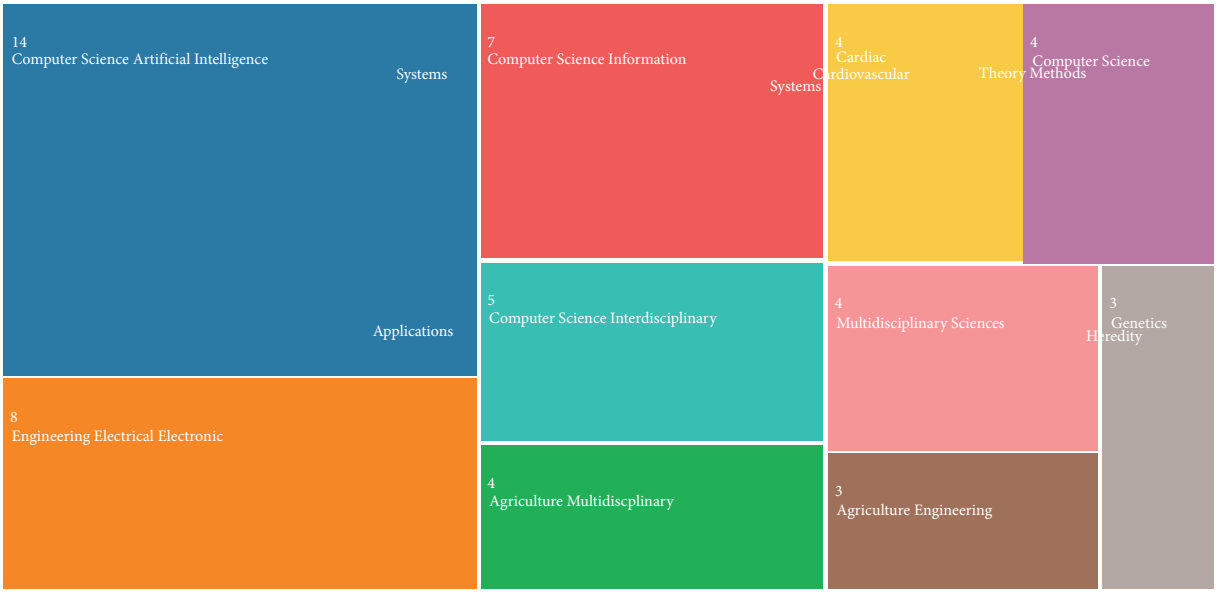

Figure 5: Source-wise analysis.

be a sharp rise in this domain and many researchers would come forward and help the farmers in saving precious rice crops from getting infected from the diseases.

3.4. Source-Wise Analysis Using Web of Science Database. Figure 5 supports the various research journals where work in the domain of rice diseases using AI is published. Computer Science Artificial Intelligence, Computer Science Information, and so on are some resources where related work can be easily found and can support researchers, globally to work further in this domain.

4. Conclusion

Computer vision and AI frameworks are now generally utilized in various stages of producing agricultural and industrial foods. Because rice plant diseases can do a big amount of loss in the agriculture domain, these frameworks can be utilized for detection of various diseases of rice crop more efficiently. Utilizing these frameworks is efficient enough to computerize relentless assignments, in a nondangerous way, creating enough information for future investigation. It was found that there are research drawbacks to be fulfilled with the design of intelligent based devices that utilize artificial intelligence computer vision for automating the tasks in the area of rice crop field. To observe the intensity of the disease, computer vision and AI techniques are very much essential. As with open eye, perception might be less accurate and it might change from person to person. At last, we aim that this review would introduce differing applications and strategies of AI, Machine Learning, and Deep Learning strategies so as to inspire more analysts who apply efficient method for taking care of agrarian issues currently open. Experiments are performed for knowledge extraction using Web of Science and Scopus databases to analyze research trends in the domain of rice disease identification using artificial intelligence using global analysis, year-wise and country-wise citations, and so on to support various researchers working in this domain.

Data Availability

The data used to support the findings of this study are included within the article. Should further data or information be required, these are available from the corresponding author upon request.

Conflicts of Interest

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

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