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A COMPREHENSIVE REVIEW ON DIAGNOSIS AND CLASSIFICATION OF PADDY LEAF DISEASES USING ADVANCED COMPUTER VISION TECHNOLOGIES

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Abstract
Food is required for human survival. Paddy is a vital food crop serving 60% of the Indian population. Food quality is determined by the plant yield. Unfavorable environmental circumstances, soil fertility, bacteria, viruses, nematodes, fertilizer use, and the absence of nutritional shortages substantially influence plant yield. As a result, it is critical to protect the plants from illness. Crop yield must be improved to meet food scarcity of growing population. Although disease symptoms are apparent in various parts of plant like leaves, stem, fruits and stem, the infections are commonly observed in the leaves. Understanding plant pathology plays a vital role in disease detection. Early detection of diseases is a prompt intervention that aids the farmers in controlling disease spread, resulting in increased agricultural quantity and quality. Image processing techniques with advanced computer vision technologies like machine learning and deep learning have proven the automation of plant disease diagnosis precisely. The main objectives of this research are to investigate computer vision technologies for the early identification of plant diseases and help novice researchers in the same domain learn about plant diseases and the methodologies for disease detection in paddy plant leaves. Consequently this manuscript reviews significant paddy plant infections, highlights related study of tools and techniques, current research, limitations and conclusions for future research in this field.

Keywords:
Paddy Disease Detection, Machine Learning, Deep Learning, Preprocessing, Segmentation, Feature Extraction, Classification, Convolutional Neural Network

1. INTRODUCTION

Agriculture is the backbone of India accounting to 60.3% of country's land area. India is a densely populated country where agriculture is the vital occupation of people. However the yield is affected by 20-30%. The early detection of rice leaf diseases is crucial [1]. Plant diseases will affect both the quality and quantity of yield. Plant yield is affected by biotic diseases, abiotic diseases and nutritional deficiencies as well [2]. Plant disease severity assessment is essential for effective crop management [3]. The knowledge of disease severity is a vital parameter in disease detection. Inaccurate disease severity assessments might lead to incorrect disease management [4].

Farmers typically detect plant diseases by observing visual symptoms. Visual observation has several drawbacks including continual plant monitoring, time consumption and need to hire experts, which add expense to farmers [5]. Sometimes their prediction may be incorrect. Incorrect prediction renders ineffective pesticide application and results in loss of yield [6]. As a result, image processing approaches are used to identify diseases including bacterial blight, brown spot, leaf blast, false smut, sheath blight, bakane [7].

Disease symptoms vary from plant to plant. Each disease is distinct in terms of shape, color and size. Some diseases might have same color, but differ in shape and vice versa. As manual disease diagnosis may lead to wrong prediction, an effective disease diagnosis mechanism is needed for the plants to assist the farmers in detecting plant disease at the early stages [8].

Plant disease management is pretty much inevitable with technological advances in digital image processing, machine learning, and deep learning. The rest of the manuscript is structured as follows: Section2 will focus on plant diseases. Section3 will reveal the related study of tools and techniques. Many researchers contributed to the fields of neural networks, machine learning, deep learning, fuzzy logic, and genetic algorithms. Section 4 will summarize the findings and section 5 will conclude the paper.

In a nutshell, the main contribution of paper includes:

- Gain knowledge of common plant diseases in paddy
- Existing dataset used by researchers
- Research gaps and issues faced by researchers
- Exploring the best use of image processing, machine and deep learning techniques in various phases of disease detection system

2. PLANT DISEASES

A plant disease disrupts the plant's normal growth and development, resulting in lower yield quantity and quality. Understanding plant pathology is the vital step of visualizing plant disease symptoms, there from researchers can develop computer vision techniques to diagnose leaf diseases. The subsequent sections 2.1 overviews plant diseases and 2.2 explore significant paddy plant diseases.

2.1 PLANT DISEASES – AN OVERVIEW

The plant diseases may be categorized into biotic and abiotic diseases. Living factors and something that is alive create biotic diseases. Bacteria, virus, fungi, protozoa and nematodes are the most common biotic disease factors. The majority of nematodes and fungi are soil borne and transmit the viruses to plant roots. Though diseases can affect both below and above sections of the soil, including stem, leaf, roots and grains, the symptoms are clearly visible in the leaves [9]. Abiotic diseases are non-infectious diseases driven by non-living factors. Temperature, rainfall, nutrient deficit, humidity, physical injuries, chemical injuries, chemical toxins, natural calamities such as lightning, air pollution are the common factors of abiotic diseases. Biotic diseases may spread throughout the plant and to the neighboring plants. Moreover they exhibit some physical symptoms. Abiotic diseases don't spread from one plant to another. The symptoms may be mild or severe [9].

2.2 SIGNIFICANT PADDY PLANT DISEASES

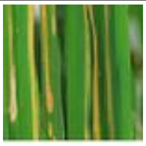
Rice blast, sheath blight, false smut, leaf scald, brown spot, bacterial leaf blight and bakane are significant paddy diseases [6]. Viruses have a significant impact on rice productivity. Rice viruses are also called "rice killer" as they cause remarkable loss in crop yield. Rice viruses replicate uncontrollably. Rice black-streaked dwarf virus, rice dwarf virus, rice gall dwarf virus, rice grassy stunt virus, rice ragged stunt virus, rice stripe virus, rice tungro spherical virus, rice yellow mottle virus are addressed in the study [10].

The Table.1 summarizes the list of all acronyms used in this manuscript. It is crucial to distinguish between two or more plant diseases that exhibit similar symptoms as well as to understand the major paddy diseases. As a result, Table.2 summarizes the significant paddy plant diseases, pathogen, and causes of disease or transmitters of disease, initial and progressive disease symptoms and their images.

Table.1. List of all acronyms

Acronym	Definition
ACISFMC	Adaptive Color Image Segmentation Using Fuzzy Min-Max Clustering
BFOA	Bacteria Foraging Optimization Algorithm
BFOA-DNN	Bacterial Foraging Optimization Algorithm - Deep Neural Network
BPNN	Back Propagation Neural Network
CAE	Convolutional Autoencoder
CCA	Canonical-Correlation Analysis
CCM	Color Correction Matrix
CMYK	Cyan, Magenta, Yellow, Key(Black)
CNN	Convolutional Neural Network
DAE	Denoising Auto Encoder
DENN	Deep Ensemble Neural Networks
DL	Deep Learning
DNN	Deep Neural Network
DNN-JOA	Deep Neural Network – Jaya Optimization Algorithm
DWT	Discrete Wavelet Transform
ESD	Ensemble Subspace Discriminative
FC	Fully Connected
FCM	Fuzzy C-Means
FDCT	Fast Discrete Curvelet Transform
FFB	Feed Forward Back Propagation
FMMN	Fuzzy Min-Max Neural Network
GLCM	Gray Level Co-occurrence Matrix
GMM	Gaussian Mixture Model
GRNN	Generalized regression neural network
HBP	Histogram Binning Pattern
HIS	Hue, Saturation and Intensity
HSV	Hue, Saturation and Value
IRRI	International Rice Research Institute.
KNN	K-Nearest Neighbour
LAB	Lightness, channel A, channel B
LBP	Local Binary Pattern
LCHR	Low Contrast Haze Reduction
MDC	Minimum Distance Criterion
ML	Machine Learning
M-SVM	Multi-Class Support Vector Machine
MUTPSO-CNN	Mutant Particle swarm optimization Convolution Neural Network.
NCA	Neighborhood Component Analysis
PCA	Principal Component Analysis
PSO	Particle Swarm Optimization
Q-SVM	Quadratic Support Vector Machine
RBFN	Radial Basis Function Network
RBKF	Radial Basis Kernel Function
RF	Random Forest
RGB	Red, Green and Blue
RKB	Rice Knowledge Bank
RMSProp	Root Mean Squared Propagation
ROI	Region of Interest
SGD	Stochastic Gradient Function
SGDM	Stochastic Gradient Descent with Momentum
SIFT	Scale-Invariant Feature Transform
SRG	Seeded Growing Region
SURF	Speeded Up Robust Features
SVM	Support Vector Machine
TNAU	University Research Centre.
TRRI	Tamil Nadu Rice Research Institute.
TL	Transfer Learning

Table.2. Significant paddy plant diseases and symptoms

Disease name	Pathogen	Cause of Disease Transmitters	Initial symptoms of disease	During progression of disease	Sample Image
Blight	Bacteria	Xanthomonas oryzae	Lesions start at the margins of the leaf blades and they enlarge, form a wavy.	Lesion change from yellow to grayish white and cover the entire leaf blade and even lead to the leaf sheath.	
Rice blast	Fungi	Magnaporthe oryzae	White to gray-green colored lesions or spots with dark green borders.	Lesions turn from white to grayish centers with red to brown or necrotic border. Lesions are diamond or elliptical or spindle-shaped.	
Brown spot	Fungi	Cochliobolus miyabeanus	Small spots or circular lesions of dark brown to purple or reddish brown or grey surrounded by dark to reddish brown border.	Lesion developed from circular to oval with light brown to gray center and reddish margin.	
Narrow brown spot	Fungi	Cercospora oryzae Miyake	Light to dark brown linear lesions on leaves which are parallel to the vein.	Usually appear in large numbers.	
Leaf scald	Fungi	Microdochium oryzae	Shows varied symptoms according to different stages. Usually, gray-green colored water soaked lesions ranges to dark brown from tip or leaf edges.	Consistent enlargement of lesions affecting large portion of leaf and wilting of leaves.	
Leaf streak	Bacteria	Xanthomonas oryzae pv. Oryzicola	Small water soaked lesion seen between veins of leaf shows dark green color initially.	Color change from green to light brown then to yellowish grey. On severity, leaves turn to brown color and die.	
False smut	Fungi	Ustilaginoidea virens	Symptoms are visible during panicle formation. Rice grains are transformed orange colored spore balls.	Turning of orange colored spore balls into greenish black spores on maturity.	
Rice stripe	Virus	Laodelphax striatellus fallen (small brown plant hopper)	The infected leaves are twisted, folded, wilted with droopy pin-sized lesions in yellow green to light orange in color.	Lesions with orange spots and upward stripe. Severe chlorosis or mottling.	
Stem rot	Fungi	Phytophthora sojae	Small and irregular black lesions appear on outer leaf sheaths at the water level.	Lesions continue to enlarge.	
Sheath blight	Fungi	Rhizoctonia solani	Oval or ellipsoidal greenish gray lesions on leaf sheath. Lesions are initially water-soaked to greenish grey.	Lesions change to grayish white with brown margins. They multiply and expand to sheath's upper part and spread to the neighboring plants.	
Rice tungro	Virus	Rice Tungro Bacilliform Virus (RTBV), Rice tungro spherical virus (RTSV).	Leaves are stunted and show mottling. Also Yellow or yellow-orange discoloration from tip to lower portion of leaf.	Small rust colored spots and inter-veinal necrosis.	

3. EXISTING TOOLS AND TECHNIQUES

This section will elaborate various methodologies employed by different researchers for image processing phases like image acquisition, image preprocessing, image segmentation, feature extraction and image classification. The Fig.1 depicts general framework for disease detection and classification using machine learning. It starts with image acquisition and progresses in stages.

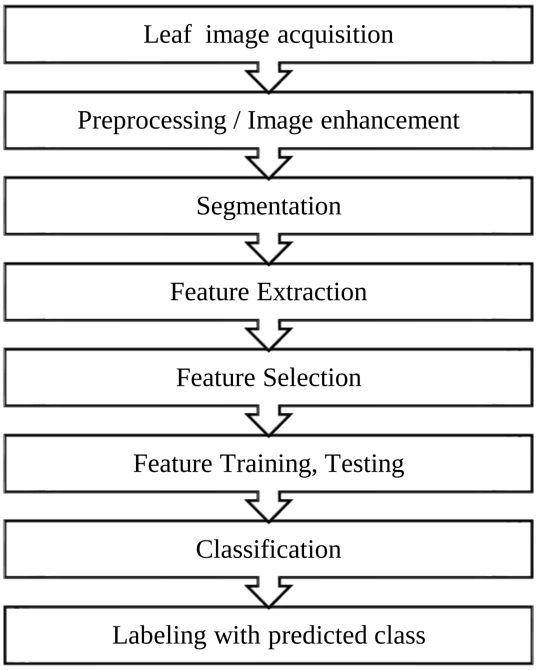


Fig.1. Machine learning Framework for disease detection and classification

3.1 IMAGE ACQUISITION

Image acquisition is the first and foremost step. It is the process of retrieving an image from multiple sources. Images are typically captured through digital camera, scanner, and high-resolution mobile phones or with a hyper spectral camera. Traditional camera can capture only three channels in light namely: red, blue and green. However, compared to traditional cameras, hyper spectral camera can capture more channels. Hyper spectral cameras capture a large geographical area using sensors and used in limited studies due to its high cost and complexity.

Table.3. Different data sources used in image acquisition

Reference	Dataset/Image acquisition location
[1]	TRRI.
[7]	Odisha rice field, agricultural pest and insect pests picture database.
[8]	From village 'Shertha' near Gandhinagar, Gujarat and related websites.
[11]	From Plantvillage dataset and Denizli city of Turkey.
[12]	From Panpoli Village, Shenkottai Taluk at Tirunelveli, Tamil Nadu.
[13]	Self collected in uncontrolled light source.
[14]	Used hyper spectral imaging system.
[15-18]	PlantVillage dataset.
[19]	UCI machine learning repository.
[20]	RKB database.
[21]	Images from IRRI database.
[22]	AI-Ghor area in Jordan valley.
[23]	Self collected using digital camera.
[24]	Collected from Ayikudi, Panpoli, Tirunelveli district, Tamil Nadu.
[25]	Own images/self collected.
[26]	Both self captured from Bangladesh and collected from internet.
[28]	From several plant leaf public databases.

Some works self-captured the leaf images using mobile camera, digital camera or hyper spectral camera. Some works have utilized public datasets like PlantVillage dataset, UCI Machine Learning Repository, Rice Knowledge Bank database, “knowledgebank.irri.org”, TRRI. Some works gathered from the agricultural field. Some works used self captured images as well as from public datasets or websites. The Table.3 summarizes different data sources used in the image acquisition.

PlantVillage dataset is the only publicly available dataset with hundreds of paddy leaf images enabling the plant disease diagnosis). But the limitation is that the images in PlantVillage dataset are taken in laboratory environment. As they are not tested in real world circumstances of crop fields, their impact in real world is likely to be minimal. This study proposes a novel dataset namely “PlantDoc” to bridge the gap between laboratory-controlled images and real world images [27].

TRRI is one of the India’s oldest research institutes. It began as a research station at Manganallur in 1912 and shifted to Aduthurai in 1922 as Agricultural Research Station. It was upgraded as Regional Research Station in 1962. University Research Centre (TNAU) was established in 1971. In 1981, Regional Research Station and TNAU were merged to form TRRI. In terms of rice varieties, there are 55 high yielding rice variants. TRRI collaborates with number of countries including Japan, Tokyo and other. TRRI performs testing lead function in rice based crop research. It also supplies first generation seeds for the new varieties to maintain the chain of seed - supply. (Tamil Nadu Rice Research Institute – Aduthurai,

UCI Machine learning repository is a collection of databases. As per the latest report in 2021, it maintains 588 datasets to serve the machine learning community. All the datasets from UCI will come with .data file extension and can be opened with notepad and MS Excel. They are comma separated (UCI Machine Learning Repository).

IRRI is the world's leading research organization dedicated to eliminating poverty and hunger by advancing rice science, improving the health and welfare of rice farmers and consumers, and sustaining the rice-growing environment for future generations. IRRI established the RKB. It offers solutions to bridge the treatment gap in rice production. Research findings, rice production techniques, agricultural technologies and best farming practices are highlighted by RKB. RKB assists to meet the most critical challenge to agricultural development by facilitating the speedy and successful transfer of technology from the research laboratory to the farmer's field. (International Rice Research Institute).

As image acquisition is a challenging step, it has prerequisites like setting orientation, proper setting of position and angle of camera and so on. Furthermore, captured data with added background has an effect on further image analysis like segmentation. Further, identified symptoms have some incomplete information, such as boundary and tissue, which complicates the process of defining the region [28].

3.2 PREPROCESSING OF IMAGE

Preprocessing of image is vital process done for enhancing quality and eliminating insignificant portion of data from the image for further analysis. Preprocessing enhances image by preserving significant details of image while removing insignificant elements. Image enhancement is possible in spatial domain and frequency domain. In spatial domain we work directly with images. In frequency domain, frequency distribution is applied over the input image and inverse transformation is applied to obtain the output image. Image filtering, resizing, clipping, denoising, color transformation, contrast editing, blurring are the commonly used preprocessing methods [29].

Contrast stretch is a form of range adjustment, dynamically. LCHR based contrast stretching improves contrast by stretching [15]. LAB color is a device independent color space transformation proposed for establishing color similarity across a variety of media device independent transformation methods [22]. HSV color space transformation contains three components: hue, saturation and value [8, 12, 17, 24]. HIS Color space is used for transformation contains three components: hue, intensity and saturation [5]. Pixel masking is done for separating required portions of image selectively based on value like color, where some pixels of an image are zero and others are non-zero [1, 5 ,8, 24, 26]. Image is resized to a fixed dimension and certain augmentation like rotation, flipping is done for improving the learning of appropriate features [7].

Filtering eliminates unwanted features from image. Different filters like low pass filter, high pass filter, band pass filter and band reject filter are used. Low pass filter is used for image smoothening, it preserves low frequency components. High pass filter is used for image sharpening and it preserves high frequency components [29]. Median filter is a non-linear and morphological filter used for removing noise [1, 13, 26, 28] and it has added advantage that it can preserve sharp features like line in an image. The Fig.2 explains various image enhancement techniques.

Gaussian filter is a non uniform low pass filter and allows fast computation. The drawback of Gaussian filter is it may not preserve image brightness. In Gaussian filter, edges are preserved and are used for removing noise [20, 25] and it is easier to use since it can be manipulated by ‘variance’ variable. Smoothing filter is a low pass filter which removes noise [30]. Image resizing is done for increasing or decreasing the pixels [7-8, 12, 21, 24, 26, 31].

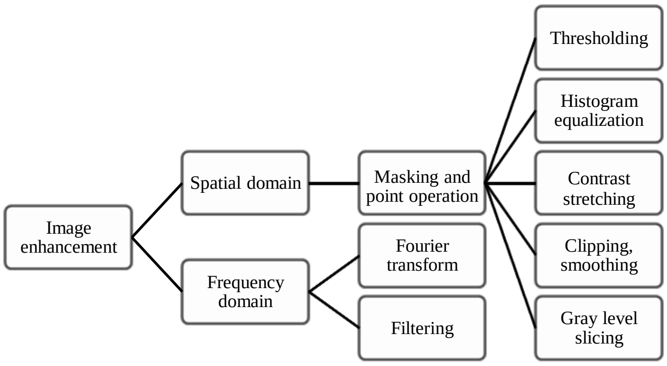


Fig.2. Various image enhancement techniques

Image clipping is done for separating or segmenting certain regions of an object from an image [20, 23]. Histogram equalization performs contrast adjustments by modifying the distribution of image intensity [18, 20]. Cropping extracts the region of interest from the actual image [8, 20-21]. Holes are generated in diseased portion as a result of noise which can be filled using Region filling technique [13]. The Table.4 summarizes various techniques used in preprocessing.

Table.4. Various techniques used in preprocessing

Reference	Preprocessing methodology used
[15]	LCHR based contrast stretching.
[22]	Color transformation structure (RGB Image), a device independent color transformation applied.
[1]	Median filter (non –linear digital filter).
[5]	RGB to HIS Color space representation, pixel masking.
[17]	RGB to HSV color space conversion and filtering.
[7]	Resized and augmented.
[23]	Clipping, smoothing and contrast enhancement.
[24]	Resizing Background image removal threshold based fusion application RGB to HSV conversion. Binary image fused with original RGB image.
[25]	Gaussians filtering and blur removal.
[18]	Improved histogram equalization.
[13]	RGB to gray scale image conversion. Median filter, region filling and unnecessary spots removal.
[30]	Smoothing filter and blurring operations.
[32]	RGB to LAB color space.
[26]	Resizing. Median filter. Contrast enhancement.
[20]	Grayscale image conversion. Clipping and cropping. Histogram Equalization process. Contrast improvement using Rayleigh Distribution Function.

[8]	Resizing. Image cropping. Background removal. Conversion to Binary image. Generating background removed image.
[12]	Image Resized. RGB to HSV conversion.
[21]	Cropping.
[31]	Image Resized.

3.3 SEGMENTATION

Image segmentation is the process of extracting a particular portion of an image for further processing and it can also be termed as extracting ROI. It is essential to observe the leaf area closely for diagnosis of diseases. Destructive and non-destructive are leaf area measurement methods. In destructive method, leaf is removed from plant and then dimensions are measured. In non-destructive method, leaf is not removed from plant for measuring dimension. Traditional leaf area measurement methods include regression equitation, grid count method, gravimetric method and planimeter. All these methods are laborious and time consuming. It is not suited for application on large number of leaves [32]. Amplitude thresholding component labeling, boundary-based, region-based approaches and clustering, template matching, texture segmentation are utilized methods [33].

Novel saliency approach, an automated image segmentation method is applied where vital information is extracted, discarding irrelevant things. The segmentation approach has four steps: LAB color transformation, best channel selection from LAB, boundary removal and dilation for additional pixel removal and finally mapping is done and ROI is drawn [15]. Images are partitioned into clusters using k-means clustering algorithm [1, 8, 12, 16-17, 20, 22-24, 26, 30, 32]. ROI is attained by segmentation followed by HSV transformation and GrabCut algorithm implementation. ‘K’ components for foreground and background region are formed, of which GMM is applied for background region. This study infers that homogeneous clusters with low variance ease segmentation process [3].

This study masks green pixels and remove masked pixels for segmentation. Based on green component of a pixel's intensity, red, blue, and green components are all set to zero. Green colored pixels are omitted as they don’t add any weight in disease identification. Removing zero valued red, green and blue pixels and the infected portion alone is extracted. The infected portion is segmented into patches of 32*32 sized pixels and selected patches with more than 50% of information are considered [5].

Genetic algorithm is used for segmentation. Genetic programming is highly famous for solving symbolic regression issues and used for solving optimizing problem. This algorithm is a parameter optimization method [23].

K-means clustering is an unsupervised algorithm for clustering, which groups unlabeled dataset into different clusters. It is an iterative algorithm that minimizes sum of distances between data points and their corresponding clusters and the value of k should be determined. The selection of k values usually follows a trial and error method and should be carefully chosen [12]. LAB color space based k-means is applied on leaf images for extracting diseased portion, yet it couldn’t differentiate diseased and non-diseased portion. The problem of cluster randomness is encountered. As a solution to this issue, k-means clustering is applied in HSV color space also evaluated using OTSU’s segmentation technique [8]. One more study used OTSU segmentation method for empirical evaluation [13]. A study concludes that image segmentation by histogram threshold can be employed for global minimum using fuzzy set detection [34].

Three thresholding methods namely global, variable threshold and OTSU method are applied for segmentation. OTSU method selects lowest point between two classes of histogram. Global threshold takes average of variable threshold. Variable threshold is manual [13].

In conclusion, it is evident that maximum of the researchers used K-means algorithm. The determination of threshold value is a vital step in segmentation. Depending on the characteristics of the data and the required level of segmentation fineness, the threshold value must be carefully selected. Incorrect threshold leads to inaccurate segmentation like over-segmentation or under-segmentation. The Table.5 summarizes various segmentation methods used by several authors in our literature survey.

Table.5. Different segmentation methods

Reference	Segmentation Methodology
[15]	Proposed novel saliency based approach.
[1,12,16-17, 22-24, 26,30- 32]	K-means clustering.
[3]	GrabCut algorithm, Orchard-Bouman clustering algorithm.
[5]	SGDM.
[8]	Lab color based k-means clustering. OTSU's Segmentation technique. HSV color space based K-means clustering.
[13]	Variable entropy, global and OTSU Thresholding.
[1]	OTSU Threshold with K-means clustering.
[23]	Genetic Algorithm.
[25]	Color based thresholding.

3.4 FEATURE EXTRACTION

Feature extraction is the next step after segmentation. In this step, extracted information is represented as a quantitative data using some mathematical notation. It is called as feature vector. The feature vector is used for analysis and further classification. A feature can be anything extracted out from image like color, texture, shape or geometrical feature [35]. Feature extraction actually reduces the number of features in an image and the amount of data to be processed. In CNN based algorithms, model should be trained but it provides more accurate results. CNN works with three dimensions namely height, width and RGB channel intensity values. For high dimensional datasets, dimensionality reduction is done for reducing the number of inputs in the given dataset. It also reduces storage space and time [17]. Feature extraction plays an inevitable role in the success of algorithm [3].

3.4.1 Color Features and Color Models:

The color features are divided into three namely: Color moment, color histogram and average RGB. As color in image is distributed, color moments namely: mean, standard deviation and skewness can be used as features to identify that image based on color. Color histogram is used for extracting color information. Average RGB is to find average of red, green, blue value components [35].

The color model represents a color with some standards. Various researchers used CMYK, RGB, HSV, HSI, LAB, etc. RGB model uses intensities of Red, Green and Blue. CMYK model uses secondary colors such as Cyan, Magenta, Yellow and Black. RGB is additive model whereas CMYK is subtractive. HSI color model deals with Hue, Saturation and Intensity. HSV deals with Hue, Saturation and Value. LAB (denoted as L*a*b*) is a device independent color model and it stands for Luminance/Lightness and two chromatic components namely A,B. Color A ranges from green to red and color B range blue to yellow. From each color model, required components are separated and statistical metrics are computed [29].

3.4.2 Texture Features:

The distribution of grey levels in an image often determines the texture of the image. We may extract two pieces of information from each pixel in the provided image: the brightness value or color depth of the pixel, and the location of the pixel. This data is used to extract statistical features.

Three methods that can be used to extract features from an image: first, second, and high order statistical methods. First order statistical features provide information regarding the gray level distribution of the image. The information is collected from the image's spectrum distribution. Second order statistical features are derived from first order feature. They typically describe the relationship between pair of pixels. The higher order statistical feature is used to measure the size of the region in the image through the pixels that have the relation brightness [36].

Mean, harmonic mean, standard deviation, kurtosis, skewness, contrast, average contrast, intensity, average intensity, lobedness, inverse difference moment, third moment, correlation, energy, entropy, variance, homogeneity, variance, RMS, inverse different moment, cluster shade, cluster prominence, uniformity, smoothness, pattern, relative strength are the various texture features extracted by different authors. Some authors made use of histogram features.

3.4.3 Shape Feature or Geometric Features

Area, perimeter, major axis length, minor axis length, extent, orientation, eccentricity, aspect ratio, elongation, solidity, stochastic convexity, isoperimeter factor, maximum indentation depth, lesion percentage, boundary color, spot color are the various shape features utilized by various works in our literature survey.

Authors propose CCA approach where color, texture and geometric features are extracted and fused. Applying NCA removes irrelevant and redundant features. CCA based fusion increases number of features, which increases computational cost and execution time is doubled as well. NCA based fusion reduces its computational cost [15]. Color space transformation is done from RGB to HSI format. Then SGDM matrices are generated for components H and S, omitting intensity values. Even if intensity is eliminated, the accuracy remains high in classification [22].

Another work utilized hybrid methods of SIFT, GLCM and DWT for feature extraction. DWT reduces image size. SIFT is for detecting salient, stable feature points. GLCM is for texture analysis [1]. One more research work used histogram, a simple to calculate feature. Image histogram, image pyramid histogram, image wavelet histogram and image wavelet pyramid histogram are used. HAAR wavelet transformation is used for image wavelet histogram. Feature selection groups all four histogram feature together and best combination is chosen for classification. Yet, the raise of histogram level will increase number of features and affects classifier's performance [19].

A study employs LBP for feature extraction. They represent local representation of texture by comparing each pixel with neighborhood matrix. LBP operator converts an image into integer matrix. Thresholding is done and weights are calculated. Contrast measure is calculated. This LBP is applied on hue channel of segmented image and it is reflected on the infected leaves, based on texture alterations caused by local changes in pixel concentration in certain bins [3].

Texture analysis is done using CCM, it is developed through GLCM. SGDM's are generated for the hue components of Image, omitting S (saturation) & I (Intensity) since they don't give any extra information. Texture features like contrast, energy, local homogeneity, cluster shade & prominence as computed for 'H'. These features are passed for classification. Shape and color features are extracted [5].

Another study uses GLCM to derive features such as energy, contrast, homogeneity, correlation, mean, standard deviation, and variance [16]. PCA algorithm is used for feature extraction [17]. Local kinds of features are extracted in the form of Eigen values and Eigen vectors. Valuable features are selected from the features using feature selection algorithm, BFOA. DL eliminates need of segmentation and feature extraction. Features are extracted automatically by pre trained network [7, 11]. We need to design the Neural Network architecture and labeled dataset [11]. A feature extraction method CCM uses color and texture of image. Contrast, energy, local homogeneity, cluster shade, cluster prominence are computed [23].

Another study extracts both color and texture features. From RGB components extracted from diseased portion mean, standard deviation are extracted. Homogeneity, contrast, correlation and energy are extracted as texture features from GLCM. Having extracted color and texture features, normalization is performed and all features are rescaled between 0 and 1. Feature extraction is done by DWT and GLCM. DWT descriptor extracts feature from images in different directions viz. vertical, horizontal and diagonal from sub bands. Correlation is computed by GLCM. Luminous level is considered by GLCM [25].

Combined features of shape, texture and color are computed. Proposed Gabor filter is created using Gaussian filter and sinusoidal function. Using GLCM energy, contrast, entropy, homogeneity is calculated. Shape features are also extracted using Curvelet transform and invariant moments. FDCT scheme is introduced. Color Texture Feature Extraction window is created which treats input image in 2D form as 1D projection. Improved performance and data reduction is seen [18].

Another study uses shape and color features. Shape features like number of objects, area of shape object, width, length, area of image are extracted. Blob analysis is used to compute statistical information such as number of object, area and perimeter. Finally lesion percentage is calculated from area of objects to area of image. Type of lesion is calculated using standard dimensions of height and width. CIElab color space extracts boundary color, spot color and broken leaf color. Color difference is calculated between color pixel and color pixel marker in terms of L^*, a^*, b^* [13].

In another study, color and texture features are extracted. From color information, mean, RMS, variance, standard deviation and kurtosis are derived. Texture features represent orientation of surface. Contrast, energy, entropy, correlation and wavelet packet entropy are derived from texture. From shape feature, diseased portion's area is extracted. After feature extraction, feature vector is created and stored in database [26]. SIFT algorithm is used for deriving important features which uses key point detection, key point location, orientation assignment and key point descriptors. Gaussian feature is used for key point determination. Mean, standard deviation, texture and shape are extracted. In feature training, extracted features are then fed into SVM [20]. SIFT algorithm extracts color and shape features [30].

One more study collects color, shape and texture features. Fourteen color features like mean, standard deviation, kurtosis, skewness are extracted. Four shape features like area of diseased portion, number of disease spots using Blob detection techniques, minimum number of obtained disease spots, and maximum area of obtained disease spots. Texture features like contrast, correlation, energy, homogeneity, cluster shade, cluster prominence are extracted. In some extended form, GLCM properties like contrast, correlation, energy and homogeneity are manipulated in 4 directions (0, 45, 90, 135 degrees) in three different planes (H, S and V) to produce 70 texture features. Altogether 88 features are extracted [8].

A fresh technique called color percentage is used. It uses only color features and needs less computation. Pixel of affected area is classified into four categories namely color A, color B, color C and color D. Percentage of each class is computed and fed into classifier [21]. Point feature matching is used where feature points are detected and feature descriptors are extracted. Then putative points are found, matching point is calculated and length of SURF points is calculated for finding infection. If the matching conditions are met, severity of disease is calculated and if the conditions are not satisfied, next disease is checked for. SURF is used here. Color, size, proximity and centroids are extracted from grey image, derived from RGB image [31].

A study uses DWT with different orientation of Gabor filter, extracts statistical features. Gabor filter detects gradual variations in leaf texture. Another Feature extraction, HBP is used to get local structure information of an image. HBP extracts statistical information [28].

In conclusion, GLCM is the most effective method for extracting texture features for classification. LBP is proven to be a valuable tool for object recognition and facial analysis. The histograms are simple to create and extract certain essential texture properties from first order image statistics [36]. The Table.6 summarizes different feature extraction methods used by different authors in our literature survey.

Table.6. Different feature extraction methods

Reference	Feature Extraction method
[15]	CCA, NCA.
[22]	CCM.
[1]	SIFT, DWT and GLCM.
[19]	Haar wavelets transform and Pyramid Histogram produces various histograms.
[3]	LBP.
[8,16]	GLCM.
[17]	PCA.
[7]	Automatic extraction from FC layers of pretrained network.
[23]	CCM.
[24]	HSV, LAB Color model, GLCM, MIN-MAX normalization.
[25]	DWT and GLCM.
[20]	Key point determination using Gaussian Filter (SIFT oriented gradient feature extracted).
[18]	Gabor filter and proposed Gabor filter using GLCM extracts texture. Curvelet transformation extracts shape, Invariant moments. Color texture projection combines color texture feature.
[30]	SIFT (shape, color feature extracted).
[13]	Blob analysis extracts shape. Boundary points and centroid point of each image is identified. RGB Color, HSI model and CIELAB color space extracts color feature.
[26]	Feature vector extracts color, texture and shape features.
[12]	Mean value, Standard deviation and GLCM are calculated. Statistical and features and GLCM properties like energy, homogeneity, contrast and correlation are extracted.
[21]	Color percentage technique calculates percentage of RGB from affected region.
[31]	Point feature matching done by SURF image comparison.
[28]	DWT and Gabor filter. HBP applied.

3.5 CLASSIFICATION

After features are extracted, the next step is classification, which categorizes a set of data into different categories or labels. Both ML and DL has a set of supervised and unsupervised algorithms. Supervised algorithms do classification and regression tasks. Unsupervised algorithms work on clustering, association and dimensionality reduction.

Classification is essential in evaluation of agricultural product, increasing market value and thereby meeting standards [1]. Classification accuracy depends on lighting, contrast and angle of capturing [21]. With advancement in hardware like GPU, the arrival of CNN architectures in 1998 and deep learning architectures really improved detection, classification and object segmentation mechanisms. TL is a novel approach implemented instead of training model from the scratch. Confusion matrix is an analysis tool is used to show accuracy of a classification model [11].

Several classifiers such as M-SVM, ESD, Q-SVM, Cosine SVM and Cubic SVM are used. Confusion matrix verifies accuracy. M-SVM outperforms by 91.4% accuracy [15]. FFBP algorithm is used by a study for classification of leaf diseases which achieves average accuracy around 93%. The model which omitted intensity has an impact in classification result among other models, since it nullifies the effect of intensity variations [22].

Another study utilized KNN, ANN, Naive Bayesian and M-SVM for classification. Performance is evaluated with the help of 500 images with 350 images for training and 150 images for testing. M-SVM outperforms with 98.63% accuracy [1]. This study has five different classifiers namely: Naive Bayesian, KNN, SVM, AdaBoost and RF. K-fold cross-validation evaluates performance and over-fitting problem overcome. It uses accuracy as performance evaluation metric. Fivefold cross-validation is used. RF is the best classification algorithm using selected features with 91.19% accuracy with 100 iterations [19].

This study used LBP histogram for training. One Class Classifier and One class SVM classifies images into target class and outliers (healthy/other), resulting in conflict resolution resolved using Nearest Support Vector strategy (that labels according to proximity). It attains 95% accuracy by classifying 44 out of 46 tested plant infections. High generalization ability with diverse leaf samples is the novelty here. Every new addition of image is fed into model, which enriches database and expanding its recognition ability. One Class Classifier is thus a flexible AI technique which leads to knowledge discovery by allowing intelligent agents [3].

This study uses MDC and SVM algorithm for classification resulting in 86.77% and 94.74% accuracy. Training and testing set of images are divided in 5%, and 95% ratio. The misclassification is due to varying plant leaf symptom: in early stages late stages. Increasing the number of training samples is the suggested solution [5]. Another study uses BPNN, classifies the disease with 92.5% accuracy. After training, performance plot, confusion matrix and error histogram are produced [16].

Another study uses three classification algorithms: Hybrid BFOA-DNN Method which produces 98% accuracy, DNN-JOA and DNN classifiers producing 97% and 93.50% accuracies. Performance metrics such as accuracy, TPR, TNR, FDR, cross entropy and FPR are calculated and compared with existing methods. It is reported that performance value of cross entropy for hybrid BFOA-DNN is 0.0011%, entropy loss value is 0.0100% and for DNN it is 0.01700%. This work can be simply extended to other leaves with minor changes [17].

This study extracts deep features from each CNN layer and feature vector is obtained. The feature vector is fed into SVM for classification. Performance of thirteen CNN models like AlexNet, VGG16, VGG19, Xception, ResNet18, ResNet50, ResNet101, InceptionV3, Inceptionresnetv2, GoogleNet, Densenet101, MobileNetv2 and ShuffleNet with different feature layers is examined. The performance of classifier is measured in terms of accuracy, sensitivity, specificity, FPR and F1 score [7].

For comparing the classification models, Tukey's honest significance test was performed. The model outperforms with ResNet50 plus SVM with 98.38% accuracy. This study is based on TL, which uses knowledge collected from an established model. But the statistical analysis report that there is no statistical significance noted with TL adaptation. AlexNet achieved highest F1 score among most used architectures and MobileNetV2 plus SVM achieved highest F1 score among small architectures. At last, traditional image calculation methods such as Bag-Of-Feature, GLCM plus SVM, LBP plus SVM and HOG plus SVM are used for calculating F1 score. The misclassification is due to closeness of color proximity of infected leaf images [7].

In first phase, MDC with K-means reported 86.54% accuracy and improved to 93.63% by MDC with proposed algorithm. In second phase, accuracy was 95.71% using SVM with proposed algorithm [23].

DNN-JOA is proposed for classification and results compared with ANN, DAE and DNN classifiers. To enhance the DNN's training speed and accuracy of classification, two hidden layers are used. Sigmoid activation function (S) is used and it is given as follows.

$$S = 1/(1+e^{-x}) \qquad (1)$$

where, x is the input data of the network.

Cross entropy (loss function of DNN) improves performance of sigmoid and softmax output models. JOA improves fitness value of every solution. Feedback loop is created to precise the stability. It is clear that DNN-JOA method attained lowest cross entropy loss. Performance metrics such as accuracy, precision, and F1 score, TNR, TPR, FPR, FDR, NPV and FNR are evaluated. Among DNN-JOA outperforms with 98.9% classification accuracy for blast disease [17].

Another study aimed to fill the research gap of optimizing loss function by comparing performance of algorithms. Study is conducted into two groups: with and without data augmentation. Proposed CNN Model, VGG16 and VGG19 (created with TL models) are used for the first phase. Next phase is training of these three models using loss functions such as Adam, AdaGrad, SGD and RMSProp optimization algorithm followed by performance comparison using loss function. Model training is then performed using epoch value, batch size and learning rate. In third phase, confusion matrix is used for performance evaluation. Accuracy, precision, recall and F1 score are calculated as evaluation metrics. In last phase, depends upon the result, model is either retrained or class prediction is performed. Results show 88% and 95% accuracy without and with data augmentation. Five-fold cross verification method is applied to data to split into training and test set [11].

Hierarchical feature extraction, a proposed method of CNN algorithm is used. Pixel value mapping and evaluation is done with trained images. FC layers are used and optimization is done on adjustable parameters of leaf region by error reduction over training dataset. The proposed method outperforms with 98.12% accuracy and is compared with AlexNet and ANN technique producing accuracy of 95.75% and 92.94% [25].

In another study, classification uses neuro fuzzy approach, fuzzy system plus neural network. Fuzzification, neural network classification and defuzzification as its phases. This classifier doesn't require any prior information about relationship among data. It has self learning, self tuning and self organizing capability and the computation is faster as well. Average classification accuracy using proposed method reported to 91.74% and reported to 93.18% with combination of shape, color and texture features [18].

This study uses production rule method where rules are framed through serial interviews with MARDI expert. Disease classification is based on lesion percentage, lesion type, boundary color, spot color and leaf color. The best accuracy rate for classification achieved is 87.5% [13]. Another study uses SVM and KNN classification algorithms with average accuracy scores of 95.5% and 92.2% [30].

SVM is used to classify paddy plant diseases. SVM is a supervised learning based classifier. It attained 90.9% for brown spot, 94.11% for leaf blast and 85.71% for bacterial leaf blight. Overall classification accuracy is 92.06%. It is compared with other classifiers such as MDC and KNN which scores 87.02% and 89.23%. This study suggests pesticides and fertilizers are based on the percentage of affected region [26]. RBFN, (A kind of ANN) takes non-linear input values and produces linear output. It uses input layer, hidden layer and output layer. Hidden layer uses Radial basis activation. BPN, RBFN, GRNN and SVM plus RBFN are used for finding mean square error value, from which SVM plus RBFN shows low mean square error value of 0.345. SVM plus RBFN outperforms by 98.3% with its average classification accuracy compared to other classifiers BPNN, RBFN and GRNN. SVM and KNN shows average accuracy rates of 95.5% and 92.2% [20].

SVM is used to generate three classification models. Model1, model2, model3 uses 88, 70 and 40 features respectively. RBKF is used for multiclass classification. Cost and gamma parameters of SVM are changed. Five-fold and ten-fold cross-validations are performed. Different values of SVM parameters have different effect on accuracy. Average lowest and highest training accuracy is 90.47% and 100%. Average lowest and highest testing accuracy is 60% and 73.33%. Improving testing accuracy will be the futuristic work [8].

Classification using ANN which uses input layer, three hidden layers and output layer. Among 300 images, training and testing uses 180 and 120 images. It shows accuracy of 99% for blast disease and 100% for healthy leaves during training phase. The testing accuracy of 90% and 86% is achieved for diseased and healthy images [12].

Another study uses Gaussian Naive Bayes for classification. Due to its simplicity and strong dependency between the features, this algorithm is chosen. The classification accuracy is above 89% for rice blast disease and above 90% for bacterial blight and rice brown spot [21]. A non-parametric classification technique, Gaussian classification technique is applied. It follows Bayesian methodology. For synthesis technique, a RBKF is used. Dataset is divided into 70:30 ratios for training and testing. Confusion matrix defines the error produced by the classifier and performance of the model. Various performance parameters such as sensitivity, specificity, CI, kappa value, detection rate, detection prevalence and no information rate are evaluated from confusion matrix. The maximum overall accuracy achieved is 99.85% for cherry leaves dataset. To ensure the consistency of classification model, dataset is divided into 50-50, 60-40, 70-30, 80-20, 40-60 and 30-70 ratios [28].

Another study uses percentage of affected area of leaf found using following equation.

$$U = (I_a / (I_a + I_u))*100 \qquad (2)$$

where I_a is white pixels of affected area and I_u is white pixels of unaffected area and U is the severity percentage of disease which is input to automatic treatment unit for appropriate dispensing of pesticides [31].

In another study, MUTPSO-CNN is proposed, which outperforms other CNN architectures in terms of accuracy, precision/recall, and execution time [37]. Another study uses variety of classifiers such as K-Means, SVM, RBF, Kernel, Optimized MLP, NN, BPNN and CNN. Classification accuracy of 99.49% is achieved for tomato leaf disease [38]. This research has a new perspective on disease characterization, where an attempt is made to classify disease based on a commonly trained deep learning model instead of trained classes of crop-disease pair [39]. Another research uses hybrid methods of CAE and CNN to classify peach leaf disease and achieved 99.35% training and 98.38% testing accuracies [40].

Another study used ML (SGD, RF, SVM) & DL methods (Inception-v3, VGG-16, VGG-19) to examine the better performing one in disease detection. Stratified 10-fold cross-validation is applied for classification. DL results are appreciable in comparison with ML. The order of classification accuracy is: RF with 76.8%, SGD with 86.5%, SVM with 87%, VGG-19 with 87.4%, Inception-v3 with 89% and VGG-16 with 89.5%. Black spot, melanose, canker, greening and canker are the labeled diseases [41].

This study proposes new technique, deep ensemble neural networks. TL is used to fine tune the models, which are pretrained. Data augmentation is applied to overcome overfitting problem. ResNet 50 & 101, InceptionV3, DenseNet 121 & 201, MobileNetV3, and NasNet models outperform. Activation functions, number of epochs, batch size, learning rate, and L2 regularizer are the hyper parameters used for performance evaluation [42].

Some performance evaluation metrics are:

- Accuracy refers to the proximity of a measured value to a standard or true value.
- Sensitivity refers to ability of a model to predict true positive of each available division.
- Specificity refers to ability of a model to predict true negative of each available division.
- The false positive rate (FPR) refers to the number of false positive results that occur among all negative samples.
- F1 score is the weighted average of sensitivity and precision.
- Precision refers to the number of true positives to sum of true and false predictions.

The formula for these terms is given as follows.

$$Accuracy = (TP+TN)/(TP+FP+TN+FN) \qquad (3)$$

$$Sensitivity = TP/(TP+FN) \qquad (4)$$

$$Specificity = TN/(TP+FP) \qquad (5)$$

$$FPR = FP/(FP+TN) \qquad (6)$$

$$F1\text{-}score = 2\times(sensitivity\times precision)/(sensitivity+precision) \qquad (7)$$

$$Precision = TP/(TP+FP) \qquad (8)$$

The Table.7 explains confusion matrix's outcome.

Table.7. Confusion matrix outcome

Outcome	Explanation
TP	True Positive, actual positives are correctly predicted.
TN	True Negative, actual negatives are correctly predicted.
FP	False Positive, actual negatives are incorrectly predicted as positive class.
FN	False Negative, actual positives are incorrectly predicted as negative class.

The Table.8 explains the summary of classification algorithms proposed in our literature review.

Table.8. Different classification algorithms

References	Classification	Best Accuracy
[19]	M-SVM, Cubic-SVM, Q-SVM, Cosine KNN, ESD.	91.4% (M-SVM) 94.1% (NCA)
[22]	FFBP algorithm.	93%
[1]	KNN, ANN, Bayesian, M-SVM.	98.63% (M-SVM)
[19]	KNN, Naive Bayesian, SVM, AdaBoost and RF.	91.19% (RF)
[3]	One class SVM.	95%
[5]	MDC and SVM.	86.77% (MDC) 94.74% (SVM)
[16]	BPNN	92.75%
[17]	Hybrid BFOA-DNN, DNN.	98%, 93.5%
[7]	Deep features with SVM.	97.62% (AlexNet +SVM)
[23]	MDC with k-means clustering. SVM Classifier.	86.54%(MDC + K-means) 97.51% (SVM)
[11]	Proposed CNN model, TL based VGG-16 and VGG-19.	95% (with data augmentation) 88% (No data augmentation)
[25]	CNN.	98%
[18]	Neuro fuzzy classifier.	91.74%
[13]	Production rule system forward chaining.	87.5% (variable threshold)
[30]	SVM, KNN.	95.5% (SVM), 92.2% (KNN).
[14]	SVM.	83.33% (jointing stage) 97.06% (booting stage) 83.87% (heading stage)
[26]	SVM	92.06%
[20]	SVM with RBFN.	SVM (95.5%) KNN (92.2%)
[8]	M-SVM, RBKF or Gaussian Kernel.	SVM - 93.33% - (training) 73.33% (testing)
[12]	ANN.	99% (Training) 90% (Testing)
[21]	Gaussian Naive Bayes.	89%
[28]	Gaussian classification.	>96.45%
[37]	MUTPSO-CNN	97.12% (training) 97.35% (testing)
[38]	CNN	99.4%
[39]	CNN	98.61% (VGG16)
[40]	Hybrid model of CAE and CNN	99.35% (training) 98.38% (testing)
[41]	CNN	89.5% (VGG16)
[42]	DENN	100%

4. DISCUSSIONS AND SUMMARY

This section of study summarizes various plant diseases in paddy and several methodologies adopted by different authors for automation of leaf disease and its classification. Start from image acquisition, different dataset used and different methods applied for preprocessing, segmentation, feature extraction and classification. The findings from several papers are listed below.

- Image acquisition is a challenging task. Most of the images are acquired by using camera, smart phones and hyper spectral images are used in limited studies.
- Images are captured in controlled environment as well as in uncontrolled environment.
- Preprocessing activities like resizing of images, cropping, color transformations and filtering are done in most of the papers.
- Traditional leaf area measurement methods such as regression equitation, grid count method, and gravimetric method and planimeter methods are laborious and time consuming. These non–destructive methods are not suited for application on large number of leaves.
- The number of features used is directly proportional to computational cost.
- K-means clustering is used by majority of researchers for segmentation.
- GLCM is used by maximum researchers for feature extraction, followed by DWT and SIFT.
- KNN shows poor performance for high dimensional data.
- Random Forest shows better performance for high dimensional data and it is an ensemble classifier.
- Naive Bayesian is best suited for image recognition and text mining.
- Classification needs prior training and it may be supervised or unsupervised.
- Training of pixels is necessary for supervised classification and training is not needed for unsupervised classification.

- SVM can handle linear as well as non-linear data and they work by transforming sample feature space by polynomial, Gaussian and sigmoid functions.
- SVM works well with all types of data, and overfitting problems are rare. Execution takes considerably less time. Cheaper computing and normalized data management. SVM is used by maximum number of researchers.
- SGD accelerates computation, converges results faster.
- RF also performs well in non-linear structures and accurately handles outliers and overfitting.
- AdaBoost (a Meta classifier) performs slightly better than random classification. It learns from iteration, penalizes for incorrect classification and newbie classifier are added to ensemble Meta classifier.
- AdaBoost is generally used to improve the performance of machine learning algorithm.
- As the dataset is small in public databases, the performance of the model may vary; hence some cross validation methods should be applied. It would be better to ensemble multiple models for fine tuning the performance.
- Data augmentation helps not only in generalizing models better but also create models that avoid overfitting and for unbalanced classification problems.
- TL helps to develop a model without training it from scratch.
- Gradual addition of filters in CNN architecture leads to model's success.
- Scout and canopy methods are used to assess the percentage of infection surface in the field.
- Python software is used by maximum of researchers for code implementation as it is open source and provides greater community support to the researchers.
- It is evident from several papers that advancements in deep learning eliminate the need for segmentation and feature extraction that is the critical part in machine learning needs more manual computations. Yet, because to its lack of interpretability, deep learning is viewed as a black box.
- Most of the researchers focused on plant diseases. While there has been significant research on plant diseases, there has been less focus on nutritional deficiencies in plants. If image recognition technology could distinguish between nutrient deficiencies and plant infections, farmers and agronomists could be able to manage and cure their crops more successfully and it is the need of the hour.

To the finest of our knowledge, very few web applications are available for identifying paddy leaf diseases. For example, Leaf Doctor, a smart phone application available for semi-automatic detection of leaf diseases and calculate severity of diseases. It has built-in camera availability. Though it has high accuracy and precision, they are restricted to black background [43]. Hence it is inevitable to develop a swift and efficient mobile application as well as web application, to predict diseases efficiently, by overcoming the existing drawbacks.

5. CONCLUSION

This study is mainly conducted for providing a comprehensive review in the area of diagnosis and classification of leaf diseases in paddy plants. Early diagnosis of disease will help the farmers for taking preventive measures. If image processing methods are properly applied, diagnosis and classification of diseases will be easier and no need of hiring any experts; which reduces cost and saves time.

To conclude, this paper discusses various paddy leaf diseases and gives fine idea about various image processing methods such as pre-processing, segmentation, feature extraction and classification. There have been seen several advancements from convolutional neural networks to deep neural networks. Various issues have been discussed and some researchers even suggest the use of pesticides for treating diseases. The performance and accuracy also depends on the dataset and how the model performs in its training and testing. This manuscript carefully has chosen reputed published works from 2013 to 2022. We conclude that our futuristic work will detect and classify the diseases in paddy leaf with computer vision technologies like machine learning, deep learning techniques which would help the farmers to automate the process of disease diagnosis efficiently and for aiding researchers in the related field.

REFERENCES

[1] T. Gayathri Devi and P. Neelamegam, "Image Processing based Rice Plant Leaves Diseases in Thanjavur, Tamilnadu", *Cluster Computing*, Vol. 22, No. 6, pp. 13415-13428, 2019.

[2] S. Kaur, S. Pandey and S. Goel, "Plants Disease Identification and Classification Through Leaf Images: A Survey", *Archives of Computational Methods in Engineering*, Vol. 26, No. 2, pp. 507-530, 2019.

[3] X.E. Pantazi, D. Moshou and A.A. Tamouridou, "Automated Leaf Disease Detection in Different Crop Species through Image Features Analysis and One Class Classifiers", *Computers and Electronics in Agriculture*, Vol. 156, pp. 96-104, 2019.

[4] C.H. Bock, G.H. Poole, P.E. Parker and T.R. Gottwald, "Plant Disease Severity Estimated Visually, by Digital Photography and Image Analysis, and by Hyperspectral Imaging", *Critical Reviews in Plant Sciences*, Vol. 29, No. 2, pp. 59-107, 2010.

[5] S. Arivazhagan, R.N. Shebiah, S. Ananthi and S. Vishnu Varthini, "Detection of Unhealthy Region of Plant Leaves and Classification of Plant Leaf Diseases using Texture Features", *Agricultural Engineering International: CIGR Journal*, Vol. 15, No. 1, pp. 211-217, 2013.

[6] P.K. Sethy, N.K. Barpanda, A.K. Rath and S.K. Behera, "Image Processing Techniques for Diagnosing Rice Plant Disease: A Survey", *Procedia Computer Science*, Vol. 167, pp. 516-530, 2020.

[7] P.K. Sethy, N.K. Barpanda, A.K. Rath, S.K. Behera, "Deep Feature Based Rice Leaf Disease Identification using Support Vector Machine", *Computers and Electronics in Agriculture*, Vol. 175, pp. 1-13, 2020.

[8] H.B. Prajapati and V.K. Dabhi, "Detection and Classification of Rice Plant Diseases", *Intelligent Decision Technologies*, Vol. 11, No. 3, pp. 357-373, 2017.

[9] G.B. Lucas, C.L. Campbell and L.T. Lucas, "*Introduction to Plant Diseases: Identification and Management*", Springer Science and Business Media, 1992.

[10] J. Qin, C. Wang, L. Wang, S. Zhao and J. Wu, "Defense and Counter-Defense in Rice-Virus Interactions", *Phytopathology Research*, Vol. 1, pp. 1-6, 2019.

[11] S. Uguz and N. Uysal, "Classification of Olive Leaf Diseases using Deep Convolutional Neural Networks", *Neural Computing and Applications*, Vol. 33, No. 9, pp. 4133-4149, 2021.

[12] S. Ramesh and D. Vydeki, "Rice Blast Disease Detection and Classification using Machine Learning Algorithm", *Proceedings of International Conference on Micro-Electronics and Telecommunication Engineering*, pp. 255-259, 2018.

[13] N.N. Kurniawati, S.N.H.S Abdullah, S. Abdullah and S. Abdullah, "Texture Analysis for Diagnosing Paddy Disease", *Proceedings of International Conference on Electrical Engineering and Informatics*, pp. 23-27, 2009.

[14] G. Zhang, T. Xu, Y. Tian, H. Xu, J. Song and Y. Lan, "Assessment of Rice Leaf Blast Severity using Hyper Spectral Imaging during Late Vegetative Growth", *Australasian Plant Pathology*, Vol. 49, No. 5, pp. 571-578, 2020.

[15] A. Adeel, M.A. Khan, M. Sharif, F. Azam, T. Umer and S. Wan, "Diagnosis and Recognition of Grape Leaf Diseases: An automated system based on a Novel Saliency approach and Canonical Correlation Analysis based multiple features fusion", *Sustainable Computing: Informatics and Systems*, Vol. 24, pp. 1-12, 2019.

[16] C. Usha Kumari, S Jeevan Prasad and G. Mounika, "Leaf Disease Detection: Feature Extraction with K-Means Clustering and Classification with ANN", *Proceedings of International Conference on Computing Methodologies and Communication*, pp. 1095-1098, 2019.

[17] A. Nigam, A.K. Tiwari and A. Pandey, "Paddy Leaf Diseases Recognition and Classification using PCA and BFO-DNN Algorithm by Image Processing", *Materials Today: Proceedings*, Vol. 33, pp. 4856-4862, 2020.

[18] A. Rao and S.B. Kulkarni, "A Hybrid Approach for Plant Leaf Disease Detection and Classification Using Digital Image Processing Methods", *The International Journal of Electrical Engineering and Education*, Vol. 23, pp. 1-9, 2020.

[19] A.A.N. Ahmed, H.M.F. Haque, A. Rahman, M.S. Ashraf and S. Shatabda, "Wavelet and Pyramid Histogram Features for Image-Based Leaf Detection", *Proceedings of International Conference on Emerging Technologies in Data Mining and Information Security*, pp. 269-278, 2019.

[20] T. Gayathri Devi and P. Neelamegam, "Paddy Leaf Disease Detection using SVM with RBFN Classifier", *International Journal of Pure and Applied Mathematics*, Vol. 117, No. 15, pp. 699-710, 2017.

[21] T. Islam, M. Sah, S. Baral and R.R. Choudhury, "A Faster Technique on Rice Disease Detection using Image Processing of Affected Area in Agro-Field", *Proceedings of International Conference on Inventive Communication and Computational Technologies*, pp. 62-66, 2018.

[22] D. AI. Bashish, M. Braik and S. Bani-Ahmad, "Detection and Classification of Leaf Diseases using K-Means-Based Segmentation and Neural-Networks-Based Classification", *Information Technology Journal*, Vol. 10, No. 2, pp. 267-275, 2011.

[23] V. Singh and A.K Misra, "Detection of Plant Leaf Diseases using Image Segmentation and Soft Computing Techniques", *Information Processing in Agriculture*, Vol. 4, No. 1, pp. 41-49, 2017.

[24] S. Ramesh and D. Vydeki, "Recognition and Classification of Paddy Leaf Diseases using Optimized Deep Neural Network with Jaya Algorithm", *Information Processing in Agriculture*, Vol. 7, No. 2, pp. 249-260, 2020.

[25] S. Ashok, G. Kishore, V. Rajesh, S. Suchitra, S.G. Sophia and B. Pavithra, "Tomato Leaf Disease Detection using Deep Learning Techniques", *Proceedings of International Conference on Communication and Electronics Systems*, pp. 979-983, 2020.

[26] F.T. Pinki, N. Khatun and S.M.M. Islam, "Content based Paddy Leaf Disease Recognition and Remedy Prediction using Support Vector Machine", *Proceedings of International Conference on Computer and Information Technology*, pp. 1-5, 2017.

[27] D. Singh, N. Jain, P. Jain, P. Kayal, S. Kumawat and N. Batra, "PlantDoc: A Dataset for Visual Plant Disease Detection", *Proceedings of International Conference on Data Science*, pp. 249-253, 2020.

[28] G. Dhingra, V. Kumar and H.D. Joshi, "Quality Assessment of Leaves Quality using Texture and DWT based Local Feature Extraction Analysis", *Chemometrics and Intelligent Laboratory Systems*, Vol. 208, pp. 1-15, 2021.

[29] R.C. Gonzalez and R.E. Woods, "*Digital Image Processing*", Prentice Hall, 2008.

[30] S. Pavithra, A. Priyadharshini, V. Praveena and T. Monika, "Paddy Leaf Disease Detection using SVM Classifier", *International Journal of Communication and Computer Technologies*, Vol. 3, No. 1, pp. 16-20, 2015.

[31] A.D. Nidhis, C.N.V. Pardhu, K.C. Reddy and K. Deepa, "Cluster Based Paddy Leaf Disease Detection, Classification and Diagnosis in Crop Health Monitoring Unit", *Proceedings of International Conference on Computer Aided Intervention and Diagnostics in Clinical and Medical Images*, pp. 281-291, 2019.

[32] R. Islam and M.R. Islam, "An Image Processing Technique to Calculate Percentage of Disease Affected Pixels of Paddy Leaf", *International Journal of Computer Applications*, Vol. 123, pp. 1-12, 2015.

[33] A.K. Jain, "Fundamentals of Digital Image Processing", Prentice-Hall, 1989.

[34] V. Singh, S. Gupta and S. Saini, "A Methodological Survey of Image Segmentation using Soft Computing Techniques", *Proceedings of International Conference on Advances in Computer Engineering and Applications*, pp. 419-422, 2015.

[35] W.K. Mutlag, S.K. Ali, Z.M. Aydam and B.H. Taher, “Feature Extraction Methods: A Review”, *Journal of Physics: Conference Series*, Vol. 1591, No. 1, pp. 1-14, 2020.

[36] A. Ramola, A.K. Shakya and D.V. Pham, “Study of Statistical Methods for Texture Analysis and their Modern Evolutions”, *Engineering Reports*, Vol. 2, No. 4, pp. 1-9, 2020.

[37] M.A. Saleem, M. Aamir, R. Ibrahim, N. Senan and T. Alyas, “An Optimized Convolution Neural Network Architecture for Paddy Disease Classification”, *Computers, Materials and Continua*, Vol. 71, No. 3, pp. 6053-6067, 2022.

[38] T. Vadivel and R. Suguna, “Automatic Recognition of Tomato Leaf Disease using Fast Enhanced Learning with Image Processing, *Acta Agriculturae Scandinavica, Section B - Soil and Plant Science*, Vol. 72, No. 1, pp. 312-324, 2022.

[39] S.H. Lee, H. Goeau, P. Bonnet and A. Joly, “New Perspectives on Plant Disease Characterization based on Deep Learning”, *Computers and Electronics in Agriculture*, Vol. 170, pp. 1-23, 2020.

[40] P. Bedi and P. Gole, “Plant Disease Detection using Hybrid Model based on Convolutional Autoencoder and Convolutional Neural Network”, *Artificial Intelligence in Agriculture*, Vol. 5, pp. 90-101, 2021.

[41] R.Sujatha, J.M. Chatterjee, N.Z. Jhanjhi and S.N. Brohi, “Performance of Deep Learning vs Machine Learning in Plant Leaf Disease Detection”, *Microprocessors and Microsystems*, Vol. 80, pp. 103615-103627, 2021.

[42] S. Vallabhajosyula, V. Sistla and V.K.K. Kolli, “Transfer Learning-Based Deep Ensemble Neural Network for Plant Leaf Disease Detection”, *Journal of Plant Diseases and Protection*, Vol. 129, No. 3, pp. 545-558, 2022.

[43] S.J. Pethibridge and S.C. Nelson, “Leaf Doctor: A New Portable Application for Quantifying Plant Disease Severity”, *Plant Disease*, Vol. 99, No. 10, pp. 1310-1316, 2015.