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A Review: Diseased Leaf Feature Extraction Using Machine Learning Classification Techniques

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Abstract

The emergence of high-performance computing and big data technologies created a need for machine learning (ML) which has led to creation of new opportunities in the multidisciplinary data intensive domains. ML has increasingly become an important field in the contemporary computing world as well as our lives. A lot of researches have been done with an aim of making the computers intelligent which has had a lot of influences in different areas of study such as language processing, medicine, agriculture and computer vision. The fast advancement of machine learning models has brought about more sophisticated tools that are capable of learning image characteristics. In terms of network design, optimization functions and training methods, the models perform differently. We present a review of machine learning approaches that are applied in diseased plant classification through use of images. The research looks at different leaf plant diseases and features extracted, the techniques utilized and how they work, the data sources employed and the general acquired accuracy performance of the techniques using the authors' metrics. The performance of the techniques is presented as well as their benefits and drawbacks. In overall, the data suggest that some techniques have excellent performance with regards to classification accuracy. However, the performance of any technique is strongly contingent on the quality of the dataset employed. Finally, potential areas and activities are suggested as future work recommendations.

Keywords: Artificial Neural Network; Convolution Neural Network; Fuzzy Logic; K-Nearest Neighbor; Machine learning; Random Forest; Support Vector Machine.

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1. Introduction

Agriculture is fundamental in human life because it is the backbone of human existence. It is directly depended on for production of food. There has been an exponential growth in population and this has brought a need to maximize food production by enhancing sustainable agriculture. The use of contemporary technologies in this field can help enhance production. Technology can promote agriculture in a number of ways by applying computer vision technology that helps establish several aspects from preplanning all the way to post harvest which may include determining the soil nutrition, timely discovery of pests and diseases, farm inputs applied such as fertilizers and herbicides [1]. All these are achieved by use of image processing. Sustainable agriculture can be realized through the use of Precision Agriculture (PA) which employs technology to improve the farming techniques. PA is the application of information technology in managing the farm by detecting, examining and handling changes that may arise in order to maximize on profits, easy maintenance and protection of the farm resources. The information technologies bring about better decision making on various aspects of the farm [2]. PA brings improved efficiency as it helps recognize and cope with any natural changes discovered in the fields in an ecologically sound way. Studies show that PA can foster long term sustainable agriculture in many ways, for instance, it decreases environmental loading by using farm inputs only when and where they are required [3] e.g., fertilizers and pesticides. Among the technologies employed by PA is computer vision in machine learning that enable precise and scalable high throughput phenotyping. Phenotyping is a practice where the physical aspects of a plant are used to make predictions. In this regard, machine learning has been applied by use of image processing to make these predictions [4]. Images to be used in image processing are acquired through real time images with satellite, cell phones, unmanned aerial vehicles (drones) and cameras. The acquired images are pre-processed then matched up so as to give more information about a plant. This information can be obtained from the color, growth rate, texture, height or shape of the plant to establish a pattern to represent the plant or farm. The analyzed information can greatly influence the managerial decision making [1]. To achieve this, machine learning (ML) techniques that exploit image data are mainly employed. ML is the application of artificial intelligence that allows computers to learn from given data by making and considering systems that enhance their own performance iteratively by design [5]. ML strategies include a learning procedure with the goal of learning from the training data so as to perform a particular task. Its performance is measured against a particular metric by use of different mathematical and statistical models. ML data comprises of a lot of marked data that is described by a collection of features. Once the ML model has been trained, it can be used to predict, cluster or classify data using test data based on the “training experience” [6]. ML performance is determined by the type of learning adopted by the model; supervised or unsupervised [6]. Supervised learning is where the researcher prepares the program to produce an answer dependent on a class with known and marked data set. Sometimes, data sources can be partially accessible with a portion of the output absent. When using a supervised model, the acquired training is utilized to forecast the missing output or labels for the test data. In unsupervised learning, the systems produce answers on unfamiliar and unlabeled data. This technique is usually utilized in establishing patterns in an array of new data [7]. Plants are subjected to stress mainly because of nutrient deficiency, pests and diseases or contamination. These plants often have visible indicators on the leaves, steam, roots, flowers or even fruits such as color variance and spots [8]. These indicators are then used by machine learning techniques to classify images to different classes by extracting image features automatically. This process is enhanced by training the ML technique with plant images to improve on classification accuracy. This review focuses on the use of ML approaches that identify diseased plant leaf images. The rationale for conducting this study arises from the fact that ML approaches have lately been used in agriculture because of their increasing popularity and success to solve diverse agricultural issues. The goal this study was to present ML techniques as a viable and high-potential solution for solving different computer vision problems in agriculture. Other than reviewing current and modern work in the agricultural domain, a practical example of the techniques utilized in identifying and classifying is provided to further highlight their merits and demerits.

2. Methodology

This study carried out a systematic literature review to establish the bibliographic study. The process entailed collecting, reviewing and in-depth analysis of relevant information on existing ML techniques in relation to plant disease classification. Journal articles, books and conference papers were obtained by using keyword-based search. Sources used in this study comprised of Google Scholar as well scientific databases such as IEEE, Springer. The search query included keywords like machine learning, deep learning, precision agriculture, leaf features for image processing, machine learning techniques in plant disease identification and classification. Papers that mentioned ML techniques but did not apply to agriculture were thus ruled out. As a result, the search was restricted to acceptable applications of ML techniques and their relevant conclusions in agriculture. To define the suitability of the techniques, the inclusion criteria was based on various aspects; PICOS (participants, interventions, comparisons, outcomes and study designs) [9], plant disease characteristics, publication status, language and years since published. The plant diseases and PICOS characteristics helped narrow down to the main area of focus. The publication status aspect ensured a reviewed article was valid and had been published not more than 10 years. The selected articles were examined one by one taking into account the problem in question, the technique utilized, data sources utilized and the overall performance accuracy. The current study focused on how the techniques performed since it would be the primary indicator of their efficacy and performance. As a result, this paper solely looks at ML approaches used in classifying plant diseases using different features of leaf images and evaluating their performance using the accuracy metric.

2.1. Data sources

The domain expertise to choose the appropriate data, time and infrastructure to obtain that data and convert it in to a form that the model can effectively recognize and learn are all required when collecting and constructing a suitable dataset. The dataset must have a large enough scale and accurately represent the use case of the model. As a result, the most logical method is to use a standard dataset that exists which sufficiently represents the problem domain. This approach has an additional benefit such that standardized datasets allow for an objective comparison, resulting in fair evaluation of the techniques based on their actual performance without selective data picking. When looking at the data sources employed in training the technique in every paper, the authors typically utilized both small and big image datasets, in some cases comprising thousands of images. Some of the datasets used were generated by the authors for their own study purposes while others were sourced from publicly and well-known accessible resources such as Flavia, Swedish, Plant Village, and UCI Machine

Learning Repository. The data sources had different number of species/classes and hence the split ratio of the training, validation and testing set were established according to the researcher's study needs.

3. Plant Feature Extraction

Feature extraction is the process of obtaining a number of elements that simply describe a big set of data uniquely and precisely [10], [11]. It is a method that constructs a combination of various variables while defining the data with utmost accuracy. Given that ML techniques rely heavily on pre-set characteristics fed into the network, feature extraction is a critical step in determining the performance quality of the machine learning technique [12]. Although various issues require different methods and procedures, there is no one extraction methodology that is regarded the optimum solution. Feature extraction is a unique method of dimensionality reduction. Its central aim is to acquire the most applicable information from the initial data and put it in a smaller dimensional space. In order to achieve the preferred assignment using the lower dimension representation, it is anticipated that the set of features will carefully extract the relevant information from the inputted data [11]. Feature extraction focuses on extracting the features that maximize the rate of recognition using the least number of attributes and subsequently produce the same features for various cases of the same data. A good set of features comprises of unique information which can differentiate objects from each other. Plant leaves can be used to identify plants and also show the diversity of plants. They are the most dominant feature, and they contain important information that may aid in recognizing and classifying any plant species just by taking a look at it. Every leaf possesses unique attributes that distinguishes it from the other. The classification of plants using leaves is based on a variety of features. Leaf feature extraction can be achieved either through region-based or contour-based extraction [12]. Contour-based uses the leaf diameter, aspect ratio, length, width leaf aspects of the leaf whereas region-based employs eccentricity, rectangularity, shape, and area. However, research points out that contour-based attributes have difficulty in obtaining the correct curvature spots [13]. Additionally, there is variation in contour of leaves even in similar species. The leaf has several features that can be used to describe it. They include leaf texture, color, vein and shape. Physiological length, physiological breadth, diameter, perimeter, and area are the five main geometric leaf characteristics [14]. From these fundamental geometric characteristics, number of other morphological digital features may be obtained.

3.1. Leaf shape

The leaf geometry defines various features with regards to shape. The shape of leaf corresponds to the aspect ratio, area and rectangularity features [15]. The shape provides co-ordinates of points such that the entire leaf area can be conveniently established through the use of convex hull algorithm. The Euclidean distance between the leaf tip (apex) and the base which makes the major axis defines the length of the leaf that is the main vein to the tip of the leaf [12]. The end-to-end distance between the leaf margins which makes the minor axis defines the breadth (width) i.e., the distance between the leftmost to rightmost side of the leaf. The diameter is the longest distance in the covered area between two points of the leaf. The length and breadth are used in finding the aspect ratio by dividing the length by the width.

$$Aspect\ Ratio = \frac{Length\ of\ the\ leaf}{breadth\ of\ the\ leaf}$$

The pixels in the image are used to calculate the area. This is done by determining the area of single pixel. $Area = Area\ of\ a\ pixel * total\ number\ of\ pixels\ present\ in\ a\ leaf$

The leaf's perimeter is the representation of the total number of pixels that appear on the leaf margin. The resemblance of a leaf to a rectangle defines the rectangularity. It is calculated as follows;

$$Rectangularity = \frac{Length * Breadth}{Area}$$

Eccentricity is a classic property that represents any conic part of the leaf. Roundness or compactness is the proportion of the surface area of the leaf to the square of its circumference.

$$Compactness = \frac{4\pi * Area}{(Perimeter)^2}$$

There are leaves with irregular shapes and irregularity (dispersion) is a feature proposed to deal with an irregular leaf shape [13]. It is however indifferent to minor incoherence in the shape for example a crack in a leaf.

$$Dispersion = \frac{max\sqrt{(x_i-\underline{x})^2+(y_i-\underline{y})^2}}{min\sqrt{(x_i-\underline{x})^2+(y_i-\underline{y})^2}}$$

Where $\underline{y}, \underline{x}$ is the leaf centroid and x_i, y_i is pixel coordinate in the leaf [16]. The dispersion formula expresses relation largest circle encircling the section and the radius of the smallest circle that may be covered in the section. Thus, as the measure grows, the section also expands.

3.2. Leaf color

The information given in color is employed to simplify the analysis of the image. The varying levels of colors of the pixels help establish the color complexity of the picture. Color moments are used to signify the color attributes in a color image. Mean (μ), standard deviation (σ), kurtosis (γ), and skewness (θ) colour moment qualities can be used [16]. The RGB color space has three features extracted from every R, G, B plane.

3.3. Leaf venation

Veins can better identify a leaf as they are unique in every plant species. The main and secondary veins are normally alike to the make-up of the entire plant. A more comprehensive property of the leaf and also that of the entire plant can be found by examining the venations [17]. Vein ramifications which are the lateral veins that arise from the main vein (midrib) are used to measure vein complexity. Morphological operations can also be employed to extract the veins with the intention of removing the background information so that only the vein patterns are visible.

3.4. Leaf texture

Texture is an attribute that partitions an image into regions of interest and then provides spatial arrangement information with regards to color and color intensities in the image. The spatial distribution of tonal variations in the neighborhood characterizes the texture. It comprises of texture elements known as texels [18]. A texel has a pixel intensity and structure features. Intensity determines the tone while the texel structure signifies the spatial connection among the texels. A fine texture results with small texels that have large tonal difference while the contrary results to coarse texture. Texture can be defined in three ways; statistical, modeling and structural. Modeling entails creating models that specify the texture. On the other hand, structural approach uses the texels in certain repeated or regular pattern. Lastly, statistical approach takes texture as a measurable aspect of the organization of intensities in a section.

4. Common machine learning techniques and their performances

4.1. K-Nearest Neighbor

K-Nearest Neighbor (KNN) is a classification method used to categorize like and unlike data into one or more classes. KNN achieves classification by establishing the closest neighbors to a given sample and then these samples are used to determine their category. It uses unsupervised mode of learning hence does not have a training process. KNN classification is determined by calculating the Euclidean distance which is the closest distance between the test and training data samples in the pattern space. This Euclidean distance established among key points helps identify related measures for the group of test data [19]. The tested sample is assigned to a class that has most shared attributes with its KNNs. this sample classification is dependent on the majority of votes the k nearest neighbors. A study carried out on 100 leaf species where three features; margin, shape and texture were extracted found out that KNN gave the accuracy of 92% on 1600 samples against Tree C4.5, KNN and Naïve Bayes techniques [20]. Kumar and his colleagues [21] extracted shape and edge features of the Flavia dataset that had 32 classes of leaves where KNN gave the overall optimal recognition accuracy of 94.37%. Munisami and his colleagues [22] extracted hull perimeter, hull area, length and width, perimeter, area, distance map, radial distance map based on centroid, and color histogram features from 32 different species with 640 leaves and obtained an accuracy of 83.5% with KNN. The accuracy increased to 87.3% when KNN was enhanced by used of color histogram. KNN is easy to implement and careful selection of features can give good results. However, KNN takes a long time to learn, especially when there is a significant amount of unlabeled data since it will have to compute the distance and sort out all the data samples at every instance. This also because it uses unsupervised learning and it is not dynamic to noisy data for large datasets. Moreover, KNN is very sensitive to irrelevant parameters [23].

4.2. Support Vector Machines

Support Vector Machines (SVM) uses supervised learning method hence it is trained by use of training data. SVM is characterized by separating hyperplane which is simply a decision boundary line. Once trained, SVM builds an ideal hyperplane which classifies the test samples. When using SVM with 2D spaces, the hyperplane is partitioned by a line and each partitioned side represents a class. The test data may fall on either side. SVM has a number of hyperplanes that effortlessly split the input dataset. The goal is to discover the side to which the data point falls on. The training data samples closest to the decision boundary are the support vectors. During the SVM training, texture feature extractions and the target values are used as inputs [24]. The test image features are given during classification. The SVM classifier recognizes the disease of the test picture by using the knowledge obtained from the training process. Sivakamasundari and Seenivasagam [24] extracted color and texture features of diseased apple leaves and used SVM as a classifier. They used mean and standard deviation to represent pixel distribution and binary bitmaps of the local color and achieved 92.67% accuracy. Srivastava and Khunteta [25] extracted 14 features using shape detector using the Flavia datasets with 16 plant species containing 480 sample images. They employed Quadratic, Gaussian and Cubic SVMs which had 90.9%, 89.4% and 89.8% performance accuracy respectively. The results showed that Quadratic SVM had the overall best performance. Kayathiri and his colleagues [26] also employed several SVM functions and Gaussian SVM outperformed the rest by 96% accuracy. Di Ruberto and Putzu [27] endeavored to build a leaf recognition technique based on color, texture and shape features using the Flavia dataset that had 32 plant species with 1907 image data. The parameters were regulated by an optimization technique for every kernel function to ensure an optimal accuracy value is obtained. The technique extracted 138 features and an accuracy of 99% was achieved. SVM classifier was used in plant discrimination using spectral reflectance measurement to develop a discrimination sensor [28]. They used weed sensors to collect different intensities of laser rays reflected by the soil and vegetation at three different wavelengths and from it, normalized difference vegetation indices (NDVI) were computed. The study utilized silver beet leaves as weed and corn leaves as a crop. The research was carried out in laboratory setup. They compared the performance of the traditional NDVI with that of SVM. The result indicated that the conventional NDVI performance did not surpass 70% as compared to the Gaussian kernel SVM whose silver beet\corn discrimination accuracy was 97%. Araujo and his colleagues[29] used multiple classifiers of Zernike Moments, Local Binary Pattern, Speed of Robust Features and Histogram of Gradients (HOG) using image from CLEF 2011 and 2012 data samples. Texture and shape features were extracted. The results showed that multiple classifiers improved performance by 28%. Khan [30] employed image segmentation and multiclass SVM to detect and classify healthy and four types of leaf diseases. The classifier performed with an accuracy of 92.8571%. Khmag and his colleagues [31] exploited spin, variant to scaling shift, filtering process and scaling approach techniques to recognize leaf images based on centroid and leaf contour. The SVM performance of 97.69% was compared to probabilistic neural networks (PNN) and it was the best performer. Mittal and his colleagues [32] used canny edge detector to extract 15 features and SVM for classification using Flavia dataset with 32 plant species. Its performance accuracy was between 85% and 87%. Sharma and his colleagues [33] extracted Gabor filter, shape and color features and performed clustering using KNN on the extracted features. SVM classified the images with an accuracy of 98.08% with a mean square error of 0.0192 which is less than of traditional SVM. SVM has high dimensional space in that the data from the input is non-linearly mapped to linearly separated data. This helps in providing effective classification performance. SVM takes full advantage of the minimal space among several classes. Kernels perform divisions on classes. SVM determines the hyper plane that divides two classes. This is accomplished by making the most of the space from hyper plane to the two classes. SVMs has robust working even when the training sets have errors thus, they have high prediction accuracy [23]. Additionally, SVMs have computational complexity that does not rely on size of the input space. SVM experiences challenges in classifying the minority class objects in imbalanced datasets. However, SVMs do not perform well with skewed data samples since getting the best possible separation hyperplane becomes difficult [34]. Also, they take a long time in training and they do not easily understand the learnt weights.

4.3. Artificial Neural Network

Artificial Neural Network (ANN) is a biologically inspired neuron. ANN comprises of various nodes, known as neurons. Neural systems are ordinarily made up of layers. In neural systems, all neurons in the input layer send signals to every neuron in the hidden layer. The constants and weights calculated during the training stage represent the biases and strengths of every signal [23]. Once the inputs have been weighted and included, a transfer function then transforms the result into an output. The direction of data processing is from the input to the output. More training is accomplished once the network recognizes the outcomes and the recognized information is forwarded to the input for weights reset with the intention of increasing accuracy [12]. Extracted features determine the input units of the network. Also, the number of plants classes determines the number of nodes the output layer will have. A method to develop an efficient baseline automated system was proposed by [35] using pattern recognition method. The study used 54 Ficus plant species leaf images with three classes. Data was pre-processed from RGB to HSV and morphological features were extracted using Histogram of oriented gradients, texture and Hu moment invariant. SVM and multilayer perceptron (MLP) with three feed-forward layers were employed for classification. ANN had the ability to recognize the image at an accuracy of 83.3% and its performance was slightly improved when area under curve was used as the evaluation criteria. Pawar and his colleagues [36] extracted textural features using first and second order statistical moments and then employed feed-forward back-propagation network for classification. The network had one hidden layer that had 28 neurons and had 80.45% performance accuracy. Random seed was used to assign initial weights so as to avoid weights randomness. The UCI Machine Learning Repository dataset was used by Pacifico and his colleagues [37] to classify plants using MLP with back-propagation technique. Margin and textures were extracted and the model had the best performance of 97.16% when the two features were combined. Individually, the margin feature had a performance accuracy of 83.29% and that of texture was 81.92%. Pujari and his colleagues [38] conducted a study on a dataset of 9912 image samples from six different classes. Imfilter and median filter were used during pre-processing while delta and threshold values were utilized during color feature reduction which were based on GLCM, HSI and RGB color models. SVM and multilayer ANN with feed-forward with back-propagation classifiers were used. SVM had a better performance of 92% as compared to ANN with 87% both when features were tested separately and when combined. Amlekar and his colleagues [39] focused on leaf venation pattern to classify leaves. 210 leaf images from four species were converted into grayscale and then canny edge detection approach was used to establish the venation pattern. Local maxima helped identify the veins. KNN and ANN classifiers were utilized. MLP architecture with back-propagation had 96.53% accuracy performance while KNN had 83%. Patil and his colleagues [40] compared Random Forest (RF), ANN and SVM classifiers using a dataset of 892 potato leaf images from which 300 images were acquired from Plant Village. The images were converted to HSV color space and then Fuzzy C-Mean clustering was used to split the diseased parts from the normal region of the leaf. ANN had an input layer with seven nodes, one hidden layer with 15 nodes and an output layer. ANN had the best classification accuracy of 92% in comparison with RF (79%) and SVM (84%). Another comparison was done by Gayathri Devi and Neelamegam [41] on KKN, Naïve Bayes, multiclass SVM and ANN classifiers. Feature extraction was attained through the usage of hybrid approach of Scale Invariant Feature Transform (SIFT), GLCM and Discrete Wavelength Transform (DWT). Median filter was used for pre-processing and K-Means for segmentation. The multiclass SVM gave the highest accuracy of 98.63% over KNN (97.5%), Naïve Bayes (85%) and ANN (94.5%). ANNs can be widely applied to a myriad of problems and they are relatively easy to use. They can learn any nonlinear function and weights that map input to an output. However, a lot of hidden units cause data overfitting problem. Consequently, the network learns extremely well during training but produces poor results [42]. It is also time consuming to build up a neural network architecture. Similarly, all neural networks have a problem of Vanishing and Exploding Gradient associated with back-propagation.

4.4. Probabilistic Neural Networks

Probabilistic Neural Network (PNN) follows a multi-layered feed-forward neural architecture that has four layers. The layers are input, pattern, summation and output layers [43]. The input layer collects the values of the training data and distributes them to the succeeding layer. The number of neurons corresponds to the dimension of the training data vector. The pattern layer computes the distance between the training dataset and the weight vector. It comprises of a neuron for every instance of the training dataset. It is also known as the hidden layer and it contains the Bayesian classifier [44]. The layer stores the predicted values for each instance together with the target value. The pattern neurons add together the values for the category they represent and forward them to the summation layer [45]. The summation layer has dedicated neurons for each category. It is responsible for summing up the results of the neurons in the same category. The output layer is also known as the decision layer. It evaluates subjective votes for every target class gathered in the previous layer and utilizes the largest vote in predicting the target class. Kulkarni and his colleagues [46] extracted color, vein, shape and GLCM textural features (energy, entropy, contrast and correlation) and combined them with Zernike moments. Radial Basis PNN with dual stage training was used for classification and attained a recognition rate of 93.82% based on Flavia dataset of 32 plant species. Fuzzy Color Histogram (FCM) for color extraction was fused together with Fuzzy Local Binary Pattern (FLBP) for texture extraction using Product Decision Rule technique so as to improve efficiency and accuracy [43]. 51 Indonesian medicinal plant species with 2448 leaf images were used and Fuzzy C-means clustering was applied for segmentation. The system offered a performance accuracy of 74.51%. Mahdikhanlou and Ebrahimnezhad [47] used axis of least inertia and centroid distance features to classify plant leaves. The Swedish and Flavia datasets with 1125 images from 15 species and 1907 images from 32 species respectively were utilized. Images were converted to binary images then canny operator was applied to detect edges. The model varied in performance with each dataset, Swedish dataset being classified at 80.1% accuracy and Flavia at 82.05% The training data is employed in calculating the probability density function and this makes PNN have a quicker training stage and classification. It requires one iteration and this makes instantaneous and easy to train. Also, the predetermination of feature characteristics makes the classification process straightforward and as a result, it is robust to misrepresentation [12]. It also requires large memory space since it stores separate weight values for each category that have different corresponding neurons in all layers.

4.5. Fuzzy Logic

Fuzzy logic (FL) is a classifier first proposed in 1965 by Lofti Zadeh and it is utilized in handling vagueness, uncertainty and ambiguity. FL employs sets of heuristic linguistic guidelines that transform imprecise and qualitative data into quantitative information. FL originates from fuzzy set theory which offer powerful tools that process and represent human knowledge. It acquires knowledge through inference and representation [48]. Its knowledge representation comprises of a collection of mathematical standards based on membership levels by use of membership functions. The process entails defining classes for each and every attribute. FL is multivalued such that it handles degrees of truth and membership. It utilizes a range of values from zero, absolutely false, to one, absolutely true. The fuzzy image processing has three major stages; fuzzification of the image, membership value modification and defuzzification of the image [49]. Fuzzy logic has been applied in plant imaging in various studies. For instance, Bin MohamadAzmi and his colleagues [49] applied FL in Orchid plant disease detection where 80 images from three types of Orchid leaves were utilized. The images were converted to grayscale, then Otsu method of thresholding applied in segmentation. Number of infected spots, centroid and area features were used. Fuzzification, fuzzy inference and defuzzification processes were used with center of area, mean of maximum and center of maximum functions. The diseases were detected on an average scale. Sannakki and his colleagues [48] used fuzzy inference with triangular membership function and seven fuzzy rules on 200 image samples. They applied Gaussian filter for noise removal and k-means clustering for segmentation and then extracted color and texture. The disease was identified on the basis of disease scoring scale, then this scale was used to grade the disease. Six fuzzy rules used for grading and all images were effectively captured as infected or healthy and then correctly graded. Cluster estimation and least square estimation techniques were combined to build a fuzzy model [50]. The model employed four Gaussian membership functions from which the minimum distance was calculated for classification. The model recognized 650 tomato and 520 eggplant images at the rate of 90.7% and 98% respectively. Mahajan and Dhumale [51] applied median filtering and Otsu algorithm in pre-processing of 57 infected leaf images. Then standard deviation, mean, skewness, extract kurtosis, entropy, and extract standard deviation fuzzy parameters were utilized. The model performed at a rate of 88% in disease detection. Another research using two plant infection; iron deficiency (96%) and fungal infection (93%) were recognized by a fuzzy model using 60 and 50 images respectively taken under natural illumination conditions [52]. Hydrangea and Maple leaves were used to detect and grade two diseases from 28 images. The percentage infection of an image was computed by a trained ANN and then FL utilized the percentage to grade the disease [53]. Fuzzy inference employed triangular membership function and a set of five fuzzy rules for grading. The model successfully graded the disease as either, very high, high, medium, low or very low risk. A research applied FL and neural networks in disease recognition by applying three classifiers namely; fuzzy inference system with subtractive clustering, multilayer feed-forward back-propagation PNN and adaptive neuro-fuzzy inference system with hybrid learning approach [54]. 13 features were computed from 180 images using CIE XYZ color space. The multilayer PNN performed better with 87.2% which was a small difference from the performance of fuzzy inference system with 86.0%. The adaptive neuro-fuzzy inference system performed poorly at a rate of 34.4% The assumptions that underly any fuzzy technique is imprecision brought by the several existing uncertainties and interpretation ambiguities. Dimensionality remains the main limitation of FL classifier since it is inadequate in solving problems with a big number of features [23]. Additionally, it performs poorly when it is supplied with inadequate amount of knowledge.

4.6. Random Forest

Random Forest (RF) is an ML approach that trains under supervised learning. It is a multi-decision tree (DT) ensemble classification technique that can handle both category and numerical data [55]. RFs are commonly used when there are a large number of training datasets and an extremely large number of input variables. A subclass of training set is randomly selected and used to generate a group of decision trees [56]. RF has two stages of classification namely; creation and prediction. Ponmalar and Krishnaveni [56] proposed a random forest classification model for medicinal plant leaves. The research used 816 leaves from 30 species where morphological and texture features were descripted. The RF classifier used sensitivity, specificity, accuracy, F1 score, precision and recall as metrics and it had a classification performance of 99%. Govardhan and Veena [57] extracted texture, shape and colour features from 140 images of eight classes using Hu moment for shape, GLCM for texture and colour histogram for colour, and RF classifier performed at the rate of 95.2%. RF has outperformed several classifiers in various studies. Caglayan and his colleagues [58] conducted a study on 1897 from 32 species from Flavia dataset descripting colour and shape features showed that RF performed at 96% precision and outpaced Naïve Bayes, KNN and SVM. Kumar and his colleagues [59] showed that RF had a predictive precision of 89.72% from 250 images of ten species where texture feature was extracted using Gabor feature extracts. Other techniques used were J48 (86.09%), KNN (79.09%) and Classification and Regression Tree (CART) with 61.63%. Hu moments for shape, Haralick texture and colour histogram were applied on 160 papaya leaf images [55]. Logistic regression, SVM, KNN, RF, and CART performances were compared and RF had an overall best of 70.14%. The study further concluded that RF can have an improved performance when the model is trained with both local and global features such as Speed Up Robust Feature (SURF), Scale Invariant Feature Transform (SIFT) and DENSE. Rahman and his colleagues [60] performed a comparative study on SVM, RF and MLP using cabbage, citrus and sorghum leaves each with 382, 539 and 262 healthy and diseased images respectively. Histogram of Oriented Gradient (HOG), statistical distribution and colour information features were utilized. F1 score was used to carry out performance comparison among the classifiers and SVM had 80.5%, MLP 94.9%, and RF was the overall best with 95.4%. Biswas and his colleagues [61] compared RF with PNN, SVM and back-propagation neural network (BPNN) and RF performed better with 86%. 900 images from grape leaves from three diseases were used. The proposed RF technique was able to detect more than one disease in a single leaf by utilizing the ensemble method. It outperformed PNN, BPNN and SVM, and had a specificity range of between 90.4 – 95.7% and sensitivity range of between 71.3 – 87.5%. The study concluded that incorporating GLCM with RF helps achieve improved and best classification performance. Random DT incorporates the pruning process in their training set. Pruning effectively overcomes the overfitting problems that is persistent in DT technique [62]. The robustness of the RF is increased by the quantity of the trees in the forest. Similarly, the accuracy of the RF classifier technique increases with the number of trees in the forest [57]. Random Forest has versatile usage, it is straightforward and it gives outcomes at faster rate. On the other hand, RFs are computationally intensive and hence, can put certain constraints on memory [58]. Inconsistency can also be experienced when either extreme or no subsampling is employed [63]. They face bias in variable selection especially where importance is given to variables with several distinct values.

4.7. Convolution Neural Networks

Convolutional Neural network (CNN) is a deep learning (DL) technique that is motivated by how the human intelligence perfect at learning different elements. DL is a neural network (NN) that has a high number of layers and it is a subset of machine learning [64]. DL is dedicated to developing techniques that clarify and acquire a high and low degree of data abstractions that conventional machine learning techniques frequently cannot. The models in DL are frequently motivated by numerous information sources and the significant number of the models that regularly mirror the essential structure of a human sensory system. The "deep" in DL originates from the numerous layers that are incorporated with the DL models, which are commonly neural systems [65]. It is based on automatic feature learning. CNNs are trainable multistage models with each stage comprising of several layers. CNN models are frequently utilized for processing data with grid-like topology such as image data that has 2D grid of pixels [66]. They are structured in such a manner to mirror the structure of the animal visual cortex. In particular, they have neurons organized in three aspects: height, width and depth [5]. Convolution in CNN implies that the network utilizes a mathematical process known as convolution which is a specific type of linear operation. They have multiple layer feature that is used to determine the output of a given data set. These layers are arranged from left to right; input, hidden which includes convolution, non-linearity, pooling, and fully connected layers. Each of these layers play a different role. A classification output is modelled after the last layer. An image is taken as the CNN input and the output is a likelihood distribution across each class. The input and output of every layer yields a 3-dimennsional array called feature maps with $d\ x\ h\ x\ w$ size, with w and h representing the spatial elements of the feature maps whereas d is the quantity of feature maps [67]. Regions in upper layers correspond to specific areas in the input picture known as receptive fields. The final output signifies the attributes obtained from all places on the input image. Each CNN layer changes the input size to an output size of node activation, ultimately resulting to the fully connected layers, bringing about a mapping of the input information to a one-dimensional feature vector. Every feature map channels out the colour contained in the input data such that if it is an image, the feature map would be a 2D array, 3D for video and 1D for audio [67]. CNN has been utilized in plant disease classification in several studies. Adhikari and his colleagues [68] proposed a CNN with 24 convolutional layers with two fully connected layers. The model used stochastic gradient descent during training with 2000 iterations to classify four classes of the tomato plant from the Plant village dataset and had an average accuracy of 89%. Pretrained GoogleNet and AlexNet CNN architectures with 25 and 145 layers respectively utilized transfer learning to classify edge and brightness features extracted from 1199 soybean leaf images [69]. Various parameters of GoogleNet and AlexNet models were modified to perform classification. AlexNet had a classification accuracy of 98.75% while GoogleNet had a performance of 96.25%. Bharali and his colleagues [70] designed a CNN with three convolutional, one max pooling and two fully connected layers to detect plant disease using leaf images. The three convolutional layers and one fully connected layer had ReLU activation function. The other fully connected layer had the Sigmoid function that was used for classification. The model was trained by utilizing the Root Mean Square Propagation and obtained an accuracy of 96.6%. Toda and Okura [71] used a CNN model based on inception V3 that had a three-input channel. The convolution layer had the ReLU function and optimization was achieved by Adam optimizer. Learning was achieved via the gradient ascent-based method where texture and colour features were utilized. A CNN approach using Fast Fourier Transform to extract edge features used a binary classifier with five convolutional-pooling layers, one dense, one dropout and one output layer that had one node [72]. All convolutional layers employed ReLU activation function and the fully connected layer had the Sigmoid function for classification. The model took 989.185 seconds in execution attaining a validation accuracy of 99% and testing accuracy of 98%. Several findings have concluded that CNNs are more powerful than just simple neural networks and hence, its performance surpasses the conventional neural networks. However, CNN requires a big number of learning iterations so that it can enhance its performance (Santoni and his colleagues 2015) and as a result, it takes longer times to train. Again, it needs large sets of data for better training and performance. There are other issues that unfold when a pre-trained CNN model is used with same and small data sets because this brings optimization issues [73].

5. Discussion

The techniques employed in the studies utilized the venation, color, texture and shape leaf feature. Three leaf features namely color, texture and shape were used by all the researchers apart from [39]. Leaf venation was employed in only two studies [39, 46]. Reference [39] utilized the veins only while [46] combined all the four leaf features. Leaf venation was the least exploited feature but its performance was impressive. Majority of the researches combined two features in their studies; either color and texture, shape and texture or color and shape. Only four studies combined color, texture and shape [27,33,55,57]. This could be attributed to the fact that these features could easily be used to establish when a plant was under stress. Further analysis is required when examining the venation of the plant under stress like checking the thinning of the veins. Most importantly, veins serve a significant role in the identification of plant species as opposed in the detection of diseased leaves. The performance of the ML techniques can be attributed to different aspects, for instance, the architecture of the technique, parameters, and dataset. The models performed exceptionally well given different training conditions. RF had the lowest performance of 70.14% was achieved by RF [55] while the highest performance of 99% was attained by SVM and RF [27], [56]. On average, CNN had the best performance accuracy of 96.1% while PNN had lowest performance of 83.46%. CNN is known to outperform the conventional ML because of the numerous numbers of layers it can contain. Additionally, the number of repetitions it is subjected to make it improves its learning hence better classification performance. Figure 1 compares how the techniques performed.

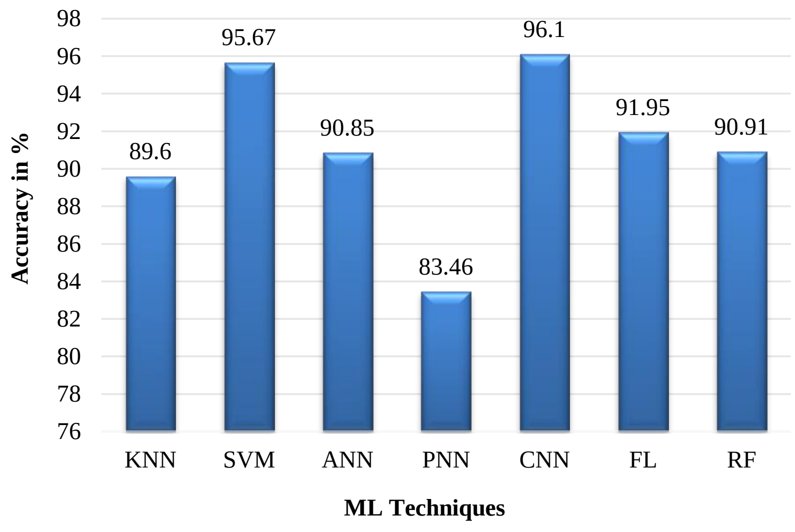

Figure 1: Performance comparison of the ML techniques

Even though majority of the authors used their own generated datasets, some of them used standard datasets which offered adequate information that can help replicate their results [21,5,27,32,46,47,58] utilized the Flavia dataset; [40,68] employed the Plant Village dataset while [47,36] utilized Swedish and UCI machine datasets respectively. There could be some constraints in the studies when researchers use their own produced data sources. In such situations, it important to consider the quality of images used as they significantly impact the performance of the technique being considered. Also, there could be no sufficient information when the results are to be replicated. Furthermore, the empirical findings presented here should be viewed with some caution due to the relatively small quantity of the datasets used by certain authors. For instance, [48] utilized 200 images, [49] used 80 images, [53] had 28 images, [54] had 180 images, and [55] employed 160 images. As a result, it becomes difficult, if not impossible, to compare techniques properly in terms of performance. The information about other metrics lacked despite the relevance of these metrics. Accuracy is the most common metric although other measures like confusion matrix, precision, recall, f1 score could be used to better evaluate the performances of the techniques. When working with training and validation sets that are not evenly split, then accuracy alone cannot be used to validate the performance of the ML technique. In such situations, accuracy misinforms the performance of the technique hence, the use of another metrics helps in providing a sound judgement. F1 score is recommended especially when working with skewed dataset split ratio. In this regard, just two authors gave information on performance indicators other than accuracy [56], [6], the rest rated their techniques with regards to accuracy. It therefore, makes it hard to ultimately compare the techniques

6. Recommendation

This study recommends that other metrics of the performance of ML techniques are considered when evaluating a technique. For instance, F1 score, recall and precision are also critical measures when evaluating the performance of a ML technique especially when dealing with unbalanced split ratio of training and validation data samples. Secondly, there is need to have parameters that inform the quantity of datasets to be used in a study. Lastly, research studies should focus on improving the classification performance by incorporating two or more techniques for the purpose of reducing computation cost.

7. Conclusion

The current paper conducted a survey of machine learning research efforts applied in plant leaf disease detection and classification. It looked at the leaf features, listed the techniques used and how they work, described the data sources utilized and reported the overall accuracy attained by each technique in various studies. The results show that the techniques achieved excellent accuracy in the vast majority of cases when they were utilized. The studies also revealed that the quality and quantity of the dataset used to train the model are significantly reliant on its successful deployment. The goal of this study was to explore the existing machine techniques in plant imaging then use them to address a variety of agricultural issues involving prediction, not only in image analysis and computer vision, but also in data analysis. This will encourage their continued use to foster sustainable agriculture and food security.

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