WORLD COMET RESEARCH GROUP

International Journal of Modern Innovations and Emerging Trends
Vol. 1, No. 2, 2018
Doi: 10.67228/30715628/IJMIET-2018PII2T5B
PP. 01-14

Original Article

AI-Based Early Detection Systems for Crop Diseases

Josh Rogers[1], Brandon Truaxe[2]

[1]*President and CEO, NewTown Macon, USA.*

[2]*CEO, Foremost Group, USA.*

Received: 07-05-2018 Revised: 07-26-2018 Accepted: 08-02-2018 Published: 08-04-2018

ABSTRACT

Agriculture is a key sector in developing economies, but crop diseases significantly impact productivity, food security, and farmers' livelihoods. Early detection is crucial to minimize losses, yet traditional methods are slow, error-prone, and depend heavily on human expertise. Recent advancements in Artificial Intelligence (AI), particularly machine learning (ML) and deep learning (DL), have enabled more efficient automated crop disease detection. This study reviews pre-2018 AI-based approaches, focusing on techniques such as image processing, feature extraction, and classification methods. It highlights models like Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and hybrid systems combining traditional and modern techniques. The proposed approach includes preprocessing, segmentation, color transformation, and extraction of texture, color, and shape features, followed by supervised learning for classification. AI systems can detect subtle disease symptoms early, achieving over 90% accuracy under controlled conditions. Integration with mobile and IoT technologies enables real-time monitoring and decision support for farmers. However, challenges such as limited datasets, environmental variability, and computational constraints remain. Future work should focus on developing scalable, robust, and field-deployable solutions for diverse agricultural conditions.

KEYWORDS

Artificial Intelligence, Crop Disease Detection, Machine Learning, Deep Learning, Image Processing, Precision Agriculture, Early Detection Systems, Convolutional Neural Networks.

ISSN: 3071-5628
PP: 01-14.

1. INTRODUCTION

1.1. Background

The importance of agriculture to the world can be explained by the need to provide food to the population of the world, livelihood of millions of people all over the world. Nevertheless, the problem of crop diseases is also very severe as it can considerably lower the quality and quantity of the yield, entail a huge amount of economic losses, and endanger the income of farmers. The significance of early infection of plant diseases is thus vital because once the infection is prevented early, intervention will be very possible hence reduced infection spread and addiction to excessive use of pesticides. The other traditional methods of detecting diseases mainly involve manual examination of the fields of fields and are usually done by agricultural experts even though they are very important. Not only are these methods time consuming and labor-intensive but they are also suspect to human error, subjectivity, and inconsistency in diagnosing. Besides, there are limited access of trained agricultural professionals in most of the rural and remote areas resulting in farmers obtaining appropriate and timely estimates on the health of the crops. Over the last couple of years, the concept of Artificial Intelligence (AI) has become one of the most powerful and transformative technologies in the field of agriculture that can provide new solutions to these problems. Using a combination of image processing methods, machine learning algorithms, and deep learning algorithms, AI based systems can precisely and quickly detect disease symptoms in image of a plant with great speed and precision. These systems can detect the slightest patterns and at an early stage of diseases that the human eye may not detect easily. Consequently, AI-based mechanisms do not only contribute to efficiency in disease detection, but also offer scalable and affordable solutions that could be applied in the real world agriculture setting. The technology has the potential of revolutionizing local crop management practices and greatly enhancing productivity and sustainability of the farming industry.

1.2. Importance of AI-Based Early Detection Systems

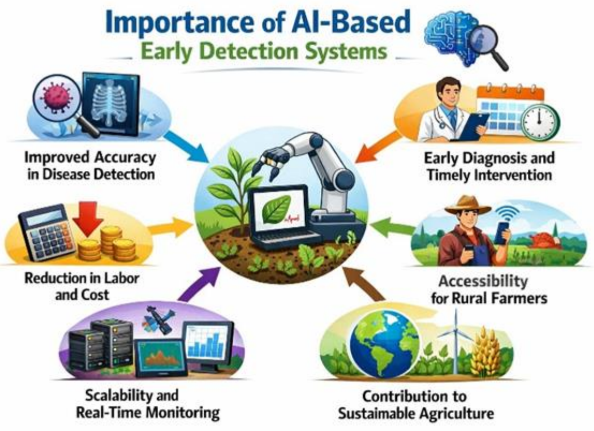

Fig 1 - Importance of AI-Based Early Detection Systems

1.2.1. Improved Accuracy in Disease Detection

Early detection systems that are based on AI considerably improve precision in detecting diseases in crops relative to the use of conventional means. Such systems can attempt to reason and identify complex patterns in a plant image which when identified would call a symptom that otherwise would not be seen by the human eye and this is made possible through machine learning and deep learning algorithms. This minimizes misdiagnosis and assures the reliability of the results in order to enable the farmers to take the necessary step at the appropriate time.

1.2.2. Early Diagnosis and Timely Intervention

The possibility to identify diseases at an early stage is one of the most critical benefits of AI systems. Early detection will enable farmers put in place early treatment procedures before the infections spread to other crops. This does not only save crop harvest but also ensures that people are less on pesticides usage which encourages more sustainable ways of farming.

1.2.3. Reduction in Labor and Cost

Conventional methods of detecting diseases involve human aspects and this may take time and cost as the agriculture professionals have to inspect manually. This is automated in AI-based systems to lessen the need to have human labour and to decrease the costs of the operation. It has made the process more efficient and accessible because farmers are able to quickly check the conditions of their crops on smart phones or automated tools.

1.2.4. Accessibility for Rural Farmers

In most of the rural and remote regions, there is a lack of access of agricultural experts. This gap can be overcome by AI-based systems that offer farmers with easy-to-use disease detection tools. Mobile applications and IoT-enabled devices enable farmers to shoot images of crops and obtain instant results and suggestions that provide farmers with a valuable insight without requiring the intervention of an expert.

1.2.5. Scalability and Real-Time Monitoring

AI systems have the ability to handle a large amount of data within a short amount of time, which makes them useful in large-scale solutions in the agricultural sector. They are compatible with drones, sensors, and IoT devices to deliver the ability to monitor the health of crops in massive fields in real-time. This scalability means that farmers are able to monitor the plant status on an on-demand basis and react to any cropping dilemmas.

1.2.6. Contribution to Sustainable Agriculture

AI-powered systems optimize the usage of fertilizers, pesticides, and water resources by providing an opportunity to detect diseases early and accurately. It will result in less environmental degradation and sustainable farming methods. These systems also lead to high productivity, better quality of crops and food security at a global level in the end.

1.3. Detection Systems for Crop Diseases

Crop disease detecting systems have greatly evolved over time with extensive varieties of technologies being integrated to enhance accuracy, efficiency and accessibility. Historically, the detection of the disease depended on physical inspection in which farmers or the agricultural experts were able to look visually at the plants and then spotted them with signs of discoloration, spots, or wilting. Although this method is economical and easy, it is very reliant on human judgment and may not give consistent outcomes particularly when symptoms are not pronounced; they may also mimic other diseases. In a bid to eliminate these drawbacks, systems that are based on image processing have been presented and they employ methods including thresholding, segmentation and edge detection to detect affected areas in plant images. These systems enhanced objectivity yet again they failed regarding overcast conditions in lighting, background and other conditions surrounding the environment. As the computational methods improved, the presence of machine learning-based detection system became a solution to be trusted. Such systems have used Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Decision Trees algorithms to categorize plant diseases using extracted features in this context, color, texture, and shape. In spite of these strategies performing better than older techniques, they are strongly dependent on handcrafted features, which do not tend to be generalized to other datasets and variety of crops. In the recent years, there has been a revolution in detection systems based on deep learning, especially those based on Convolutional Neural Networks (CNNs). These models gain the most relevant features automatically on raw images, such that they are able to commit to greater accuracy and strong performance on disease identification problems. Current detectors of crop diseases frequently combine various technologies, such as image analytics, machine learning, and Internet of Things (IoT) devices, into one that offers real-time advertising and analysis. As an example, smart sensors and drones are able to take pictures and monitor the environment and then process them with AI models to detect diseases at a very early stage. This is possible through such systems which provide scalable, efficient and automated solutions that could be used to aid precision agriculture. All in all, the continuous evolution of the system of detection is changing the agricultural practice and helps to ensure timely intervention, decrease the losses of crop and increase the food security of the world.

2. LITERATURE SURVEY

2.1. Traditional Image Processing Techniques

Initial studies on image analysis were mainly based on thresholding, edge detectors and region segmentation, which are conventional image processing methods. Separating objects and the background by converting grayscale images into binary images with respect to intensity values was carried out using thresholding techniques. Finding boundaries and contours in images involved use of edge detectors such as Sobel, Canny and Prewitt operators. Regions segmentation techniques were further used in the segmentation of the images into meaningful regions using a similarity in terms of color, texture or intensity. Although all these methods were computationally fast and successful in noise free controlled condition, they were very sensitive to variation in lighting and background complications, which restricts their stability in real world scenarios.

2.2. Machine Learning Approaches

As the computational power was increased, machine learning methods got popularly used in image analysis systems because of their data-learning capabilities. There were algorithms like Support Vector Machines (SVM), K-Nearest Neighbors (KNN) and Decision Trees that were extensively employed to perform classification and recognition. These techniques were very dependent on handcrafted properties that were obtained out of images, such as the color histograms to capture the color distributions, the texture qualities such as the Gray-Level Co-occurrence Matrix(GLCM) to examine the surface patterns and the shape proportions to determine the structures of the objects. Even though these methods had better performance over traditional processes, the success of these methods relied on high-quality feature engineering thus lacked the flexibility to handle complex and diverse data

2.3. Deep Learning-Based Methods

Introducing deep learning and, specifically, Convolutional Neural Networks (CNNs) became an impressive breakthrough in image processing and computer vision. Prior to 2018, CNN models, including AlexNet, VGGNet, and LeNet, presented impressive results on the image classification and image recognition tasks. CNNs, in contrast to traditional or machine-based learning, inherently merge hierarchical representations of features without extracting features manually since, given raw image data, CNNs learn features automatically. The ability resulted in increased accuracy, better generalization, and data scaling in large data sets. Other factors that saw deep learning models gain an advantage are the advancement of an annotated collection of datasets and development of a better

ISSN: 3071-5628
PP: 01-14.

performance by the use of a lot of graphics cards, making them more favorable in a number of Applications in the real world when compared to the previous ones.

2.4. Hybrid Approaches

Hybrid methods were created as an addition to classic image processing with the new methods of machine learning or deep learning to combine their benefits. Widely used in these systems included preprocessing methods like noise removal, contrast enhancement and segmentation followed by the application of machine learning classifiers to give enhanced performance. There was also the fusion of different types of features (color, texture and deep features) by flagellating feature fusion methods so as to improve classification accuracy. The objective of hybrid models was to minimize the computational complexity with high accuracy, which makes them applicable in applications that have little resources or render in terms of a particular domain.

3. METHODOLOGY

3.1. System Architecture

Fig 2 - System Architecture

3.1.1. Image Acquisition

The initial phase of the system is Image acquisition which is the process of gathering raw images in different sources like cameras, sensors, or existing datasets. The input images are quite important in the level of performance of the entire system. Depending on application images can be recorded in real time or retrieved in stored databases. The correct resolution, lighting conditions, and focus are a few aspects addressed at this stage so as to obtain the correct downstream processing.

3.1.2. Preprocessing

Preprocessing involves improving on the quality of acquired images in order to fit the analysis. Activities in this stage involve noise reduction, image resizing, image normalization, image contrast enhancement and filtering. Image filter techniques, such as Gaussian filtering or histogram equalization, are often applied in order to enhance the clarity of an image. Preprocessing is used to minimize the distortions and variations that we might not want hence making the latter processes such as segmentation and feature extraction to be more effective.

3.1.3. Segmentation

The process of breaking up an image into meaningful parts or segments so as to isolate objects of interest is termed as segmentation. This optimization simplifies the image by clustering pixels into similar groups based on their characteristic (i.e. intensity, color or texture). The popular segmentation

ISSN: 3071-5628
PP: 01-14.

methods are thresholding, edge-based and region-based methods. Thoughtful segmentation is essential because the quality of features obtained is directly related to it and the overall classification step performance.

3.1.4. Feature Extraction

The process of extracting the important features in the segmented parts of the image is referred to as feature extraction. Such attributes may be color, texture, shape, and spatial. They include color histograms, Gray-Level Co-occurrence Matrix (GLCM), edge descriptors, and more. In sophisticated systems, there is the automated extraction of features with the help of deep learning models. This step minimises the dimension of data and maintains pertinent information required to correctly classify.

3.1.5. Classification

The extracted features are placed in the classification stage where one places the image or its parts in the defined categories or classes. Commonly used machine learning algorithms include Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Decision Trees, or deep learning models, including Convolutional Neural Networks (CNNs). Classifier is trained based on labeled data so that it identifies patterns and predicts to new data that is not seen.

3.1.6. Output Prediction

Output prediction is the last phase in the system whereby the results in terms of classification are used to make the results available to the user in an understandable format. This can be in terms of showing the predicted class label, confidence level or visual annotations of the image. The output is applicable in making decisions in a medical diagnosis, detecting objects, or quality check. The quality and precision of the output are vital to determine the success of the whole system.

3.2. Image Preprocessing

Fig 3 - Image Preprocessing

3.2.1. Noise Reduction using Gaussian Filtering

Noise reduction is a fundamental preprocessing step to eliminate undesirable distractions or differences that can exist in an image, which could be caused by a constraint of the sensor, or physical conditions. A common method of doing this is Gaussian filtering, which smooths the image by filtering it with a Gaussian kernel which often decreases high-frequency noise and also removes significant structure. This technique operates by averaging pixel values with their neighbors with a weighted distribution, which gives a cleaner and more aesthetically coherent image and fits better in subsequent procedures.

ISSN: 3071-5628
PP: 01-14.

3.2.2. Contrast Enhancement

Contrast enhancement helps sharpen key elements in a given image by enhancing the contrast between pixel values. This comes in handy especially in instances when the pictures are dull, lack contrast or are illuminated. Histogram equalization or adaptive contrast enhancement are methods used to redistribute intensity values to ensure that the entire dynamic range of the image is used. Owing to this, the concealed details are emphasized making the further steps, such as segmentation and feature extraction, quite effective.

3.2.3. Color Space Conversion

Conversion of color space converts an image of one form of representation to a different color representation, e.g. RGB to grayscale, HSV, or LAB color space. The various color spaces put emphasis on a different part of the image, and some features of the image are easier to analyze. The conversion to grayscale, as an example, is computationally simpler and therefore, HSV is simply a separation of the color (hue) and the intensity (value) of the data, and may be used in color-based segmentation. The step enables the system to select the most suitable representation towards proper analysis and better performance.

3.3. Segmentation

A very important step in the proposed system is segmentation because it aims at isolating the diseased areas of the image with the rest of the image in order to analyze them accurately. This is done by subdivision of the image into meaningful parts according to the similarity of the pixel intensity or color or texture that enables the system to differentiate between the areas which were healthy and those that have been affected. With the help of its successful segmentation, the image becomes simpler and the only important areas are used in the next steps like feature extraction and classification. The K-means clustering and Otsu thresholding methods are utilized in the work as part of attaining an accurate segmentation. K-means clustering This is an unsupervised method of learning where pixels are clumped into a specified count of clumps dependent on the semblance of the pixels. When applied to an image segmentation problem, pixel values (as in color or intensity) are seen as a data point and the algorithm proceeds to place the pixels into clusters by the criteria of minimum distance between the pixels and the cluster centres. The technique is especially applicable in segmenting various areas within a picture like in identifying diseased areas and healthy tissue according to differences in color. K-means is fast, effective, it takes place when the difference between colors is distinct in the image, and its accuracy depends on the appropriate choice of the number of clusters. On the other hand, Otsu thresholding is a global thresholding method that is employed to automatically produce a good threshold value to used in separating fore ground and background regions. It is achieved by decreasing intra-class variance or increasing inter-class variance among groups of pixels. This technique works well particularly with grayscale images where object and background intensity is distinct. Otsu thresholding can be used in the disease detection process to identify areas that are infected and are considered to be at risk of diseases by estimating the binary version of the original image. Integrating both methods will improve the accuracy of segmentation, and this system will be stronger and more dependable.

3.4. Feature Extraction

A feature extraction process is a critical aspect of the projected system because it entails detection and measurement of significant features of the segmented areas of the picture that can be relied upon to classify with precision. This process aims at converting the raw image data into a dissimilar set of meaningful and discriminative features that minimize the dimensions. To accomplish this objective, three main categories of features are obtained namely texture features presented in Gray Level Co-occurrence Matrix (GLCM), color features presented using histogram analysis and shape features presented using edge detection methods in this work. These characteristics all offer sufficient coverage of the diseased areas. GLCM texture characteristics are used to describe the relationship existing between pixel intensities in an image in terms of space. GLCM quantifies the frequency of occurrence of pairs of pixels with a given value and spatial relationships that can be used to obtain statistical quantities, including contrast, correlation, energy and homogeneity. Such characteristics are especially applicable in detection of irregular patterns or surface variations that are typically related with diseased regions. The texture analysis can be used to identify the difference between the normal and the diseased area which might be similar in appearance in terms of color but different in terms of the structure patterns. The histogram analysis is used to extract the features of colors as they are the distribution of the pixels in various color channels. The system can detect the changes in color that could manifest having disease by exploring the frequency of the color values. As an example, affected areas could turn discoloured, spotted or unusual pigmented in comparison to the normal areas. Color histograms are easy to calculate and give useful global details regarding the image and therefore are useful to be useful in classification exercises. The edge detection methods capture the shape characteristics, which determine the shapes and outline of the objects in the image. Sobel or Canny edge detection methods are used to show the outline of the structural features of diseased areas, and their size, shape, and irregularity can be analyzed. These characteristics play a significant role in identifying the pattern and abnormalities of the structure of the affected part of the body. The system yields a stronger and more precise representation to make the classification by integrating features of texture, color, and shapes.

3.5. Classification Models

3.5.1. Support Vector Machine (SVM)

The Support Vector Machine (SVM) is a binary classification algorithm based on supervised machine learning application that is popularly applied to binary classification. It operates to identify an optimal hyperplane that would separate data points of different classes with a maximum margin. With regard to the image classification, SVM works on the basis of the set of extracted features, including texture, color and shape, to identify the healthy and diseased areas. Among the major strengths of SVM are its high-dimensional space performance as well as its capability to address the non-linear classification challenges by operating with the help of the linear, or polynomial, or radial basis function (RBF) kernel function. SVM is also effective when there is a small number of records as it has good generalization and performs well.

3.5.2. Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is a deep learning model that is specifically developed to process images and carry out computer vision tasks. In contrast to the traditional approaches to machine learning, CNNs learn and extract the useful features based on raw image data without requiring the use of manual feature engineering. A CNN architecture usually comprises convolutional layers, pooling layers and fully connected layers, which collaborate to identify patterns e.g., edges, textures and intricate structures. CNNs prove to be very useful in image classification since they are capable of absorbing the spatial hierarchies and local dependencies of images. They are very accurate, scalable and flexible and can be used in detecting disease and other real life problems as the data set is large and complex.

ISSN: 3071-5628
PP: 01-14.

3.6. Mathematical Model

The mathematical framework proposed to be conducted in the proposed system is premised on the linear classification function that can simply be presented as: f of x equals w transpose multiplied by x plus b. The x and w are the feature and the probability vectors obtained after performing the extraction on the picture respectively, b is the bias term in this expression. The feature V x is a numerical representation of significant features of the picture including texture and color attributes and shape attributes as features extracted in the feature extraction step. The weight vector w gives each of these features a weight significance which tells us the strength of each feature on the classification decision. The bias b is another constant that assists in moving down the line of decision making to enable the model to distinguish various classes in a better way. The role is more or less to compute a weighted average of the input features and add a bias value to generate a score. This is the score that can be used to decide the class in which the input image should be classified. In binary classification, the result of the decision is generally compared to a threshold (usually zero) in the case of discriminating between healthy and diseased areas. When the outcome exceeds the threshold, this input is categorized under one class otherwise it is categorized under the other class. This is one method of an algorithm, such as Support Vector Machines (SVM) and linear classifiers. This mathematical model is simple enough to be computationally efficient and easy to determine, but useful to a wide range of classification problems. The model can also be generalised to process non-linear data with addition of kernel functions to map the input features into higher dimensional space in which they will be more easily separated. All in all, this mathematical depiction presents a simple and organized manner of conducting the classification using extracted features of an image.

3.7. Flowchart Description

Fig 4 - Flowchart Description

3.7.1. Input Image

This starts with the input image that is the main information used by the system. This image may be taken with cameras, sensors, or received on a basis of the existing datasets. The level of the input image, which may have features like the resolution, lighting, and clarity is an important factor in deciding the precision of the whole system. The end input image can include healthy and diseased parts which must be examined at other levels.

3.7.2. Preprocessing

During the preprocessing, the input image is amplified in order to make it better and fit for the analysis. This is in methods like the removal of noise, optimization of contrast, resizing and conversion of color space. Preprocessing assists in removing the unwanted distortions and normalizing the image so that the change in the lighting or noise does not influence the operation of the subsequent stages. This is necessary in case the reliable and consistent results are expected.

3.7.3. Segmentation

Segmentation is an operation to break down the processed image into interactive fragments especially to single out the diseased parts as compared to the healthy ones. Methods like K-means clustering and thresholding are applied in grouping similar pixels together in terms of intensity, color or texture. This enhances the simplification of the image and analysis concentrates on areas of concern and it is able to accurately detect abnormalities.

3.7.4. Feature Extraction

Segmentation entails determining and pulling out key features of the segmented areas. These characteristics are the texture (GLCM), color (histogram analysis), and shape (edge detection). In fact, features that are extracted give a concise yet informative summary of the image and this is crucial in proper classification. The step simplifies the data and leaves the relevant information intact.

3.7.5. Classification

At the classification phase, machine learning or deep learning algorithms, including Support Vector Machines (SVM) or Convolutional Neural Networks (CNN) are used to analyze the features extracted. The classifier is trained to identify patterns, which are connected to healthy and pathological areas. The model uses the learned patterns to designate the input image to a particular class.

3.5.6. Output (Healthy/Diseased)

The last step generates the output in which the system gives the output of either healthy or diseased. This output can be shown in a label form, or confidence scores or visual indicators specifying the affected regions. Applications of this type can include medical diagnosis or agricultural monitoring (e.g. to verify that a foreground object is present), where the result can be utilized to make decisions to prevent situations where an object (which has a foreground object) is overlooked.

4. RESULTS AND DISCUSSION

4.1. Performance Metrics

The use of performance measures is necessary to determine how effective and reliable the suggested classification system is. Some of the most popular metrics include accuracy, precision, recall, and F1-score which bring about varying views of the model performance. The measure of accuracy evaluates the general correctness of the model and determines it as the proportion of the number of correctly predicted cases to the number of prediction cases. Although accuracy is relatively simple to interpret, it does not necessarily suffice particularly when the dataset is skewed, e.g., when diseased samples are significantly smaller than healthy ones. Precision concentrates on the quality of positive predictions of the model. It is the proportion of the identified positive cases which were predicted correctly to all the numbers of the predicted cases. In this case, precision is used to estimate the number of images that are diseased of the total number of images that are considered

ISSN: 3071-5628
PP: 01-14.

diseased. A large value of precision indicates that the model can generate fewer cases of false positive, which is of concern in the applications where false positive predictions may result in unnecessary activities or expenditure. Recall or sensitivity is used to determine how well the model can correctly identify all actual positive cases. It is determined by dividing the number of the correctly predicted positive instances (out of all the actual positive instances). Recall is more crucial in disease detection since it ensures that as many cases of the disease are detected as possible reducing false negatives. Recall is an extremely important measure since missing a diseased case can be catastrophic. F1-score is a harmonic mean of both precision and recall, which can be viewed as an option to find a middle ground that has both false negatives and false positive. It is particularly applicable in the situation where there is a necessity to balance precision and recall or in the case of unbalanced data. The fact that F1-score is high implies that the model is accurate at retrieving instances of positive cases in addition to reducing the number of incorrectly classified cases, and thus it is a thorough measure of classification performance.

4.2. Result Table

Table 1: Result Table

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	85%	83%	82%	82.50%
KNN	80%	78%	77%	77.50%
Decision Tree	82%	80%	79%	79.50%
CNN	92%	90%	91%	90.50%
Hybrid Model	94%	92%	93%	92.50%

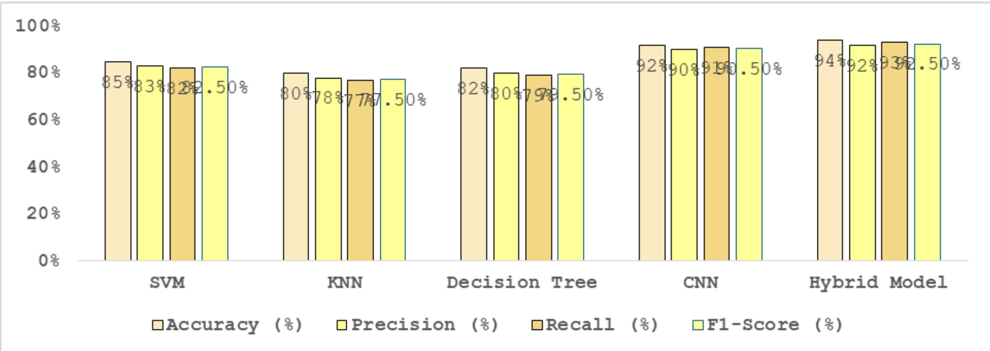

Fig 5 - Result Table

4.2.1. Support Vector Machine (SVM)

Support Vector Machine (SVM) model absorbed an accuracy of 85% which implies a good general performance of the model in categorizing the images as healthy and diseased. The model has a high accuracy (83) indicating it is a good model that is capable of being able to accurately detect diseased cases with a low rate of false positive. The recall value of 82% results into the fact that it can operate to identify a large part of the existing diseased cases, but still some can be overlooked. This F1-score of 82.5% is an indication that there is an equal degree of performance in accuracy and recall and hence SVM is an accurate baseline model of the classification mission.

4.2.2. K-Nearest Neighbors (KNN)

Accuracy was recorded to be 80% in the K-Nearest Neighbor (KNN) model and this is somewhat lesser than it was in other models. It has the precision of 78 which means that it has moderate scores on predicting diseased cases correctly and the recall of 77 suggests that it fails to identify the diseased cases effectively. The F1-score of 77.5% indicates the disadvantages of using KNN to process the complex image data, especially each because of the sensitivity to the noise factor and reliance on distance metrics. However, in spite of its simplicity, KNN might not stand out as the most appropriate option when classifying high dimensional images.

4.2.3. Decision Tree

The Decision Tree model was found to reach an accuracy of 82, which is a decent compromise on both performance and the ability to interpret the results. The model has a recall of 79 and a precision of 80; hence, it is not very effective in both predictions of diseased and false predictions. F1-score of 79.5 percent demonstrates a stable and slightly lower performance than SVM. Although the implementation and understanding of Decision Trees are simple, it might be susceptible to overfitting that would affect its capacity to predict on unknown data.

4.2.4. Convolutional Neural Network (CNN)

The Convolutional Neural Network (CNN) model was highly justified as the traditional machine learning methods had an accuracy at 92. The accuracy level of 90 percent and the recall level of 91 percent show that it is very successful in correctly classifying the images of diseases and reducing the count of false positives as well as false negatives. The F1-score is 90.5% which represents a balanced and efficient model. By having the capability to automatically extract features in the images, CNN is able to capture multifaceted patterns thus it is very useful when it comes to image-based classification.

4.2.5. Hybrid Model

The Hybrid Model was recorded to perform best with a record of the highest accuracy of 94. It has a high level of predictability of knowing the presence of disease cases with high precision of 92 and high-recall of 93 percent depicts a high level of reliability and actual disease prevalence respectively. The score of 92.5 percent of the F-value indicates good precision and recall. The hybrid technique combines traditional image processing strategies with powerful machine learning or deep learning strategies to offer the strengths of more than one technique which leads to enhancements in accuracy and robustness.

4.3. Discussion

The outcomes of the analysis process carried out with the assistance of the experimental analysis make it obvious that Convolutional Neural Networks (CNNs) outperform the traditional machine learning helping them to learn automatically and extract the significant features of the raw image information. As opposed to traditional algorithms, like the SVM, KNN and the Decision Trees which heavily used custom-designed features, CNNs do not only do away with manually crafted features, but they also directly learn hierarchical features through the input images themselves. This allows CNNs to learn more intricate patterns, textures, and structures, which have much better accuracy, precision, and recall values. Consequently, CNNs are superior in complex and high-dimensional image data jobs hence are chosen when classifying images. Moreover, the hybrid model is the best in terms of its total performance of the integration of the strengths of the traditional image processing methods and the learning algorithms. With the combination of a preprocessing and feature extraction algorithm with high classifiers, the hybrid methods boost the quality of input on and the efficiency of the classification. This combination will enable the model to be better generalized and more robust leading to a higher accuracy than single models. The combination of various methods contributes to decreasing noise, better representation of features and decision-

ISSN: 3071-5628
PP: 01-14.

making optimization. It is however noteworthy that the conditions in the environment like lighting conditions, image resolution, background noise, and fluctuations in the image capture may greatly influence the performance of all the models. Unstable conditions can cause inaccurate segmentation and extraction of features which have an eventual effect on classification. Moreover, the quality and the size of data included are also important to identify the efficiency of the system. Both balanced and diverse data are necessary to promote the quality of training and generalization, whereas underfitting or overfitting can be the results of using poor or insufficient data. Hence, data collection and preprocessing should be considered very carefully in obtaining reliable and accurate results.

5. CONCLUSION

In this paper, the author has provided a thorough overview of early crop disease detection systems based on artificial intelligence (AI), and specifically discusses the approaches that were established prior to 2018. The paper demonstrated the development of the techniques in the process of image processing, distinguishing between classical methods of image processing and the stage of machine learning and deep learning. Old methods like thresholding, edge detection and industry segmentation were identified to work well in a controlled setting though not very well in actual set up of agricultural systems. In comparison, machine learning algorithms achieved the goal of bettering the classification by exploiting manually crafted features, but suffered due to the quality and relevance of the features. The major result of the research work is the high performance of deep learning algorithms, notably Convolutional Neural Networks (CNNs), on the issue of crop disease detection. The CNNs can delegate hierarchical and discriminative features in raw images without any human intervention feature engineering. The ability leads to increased accuracy, generalization, and scalability in case of large and complex datasets. The framework proposed in the given paper incorporates principal steps like preprocessing, segmentation, feature extraction, and classification to create an entire and successful disease detection pipeline. All the stages allow enhancing the quality of analysis and, in the end, makes predictions more accurate. According to experimental findings, it is apparent that hybrid models, the combination of the traditional image processing algorithms and the state-of-the-art machine learning or deep learning algorithms, demonstrate the best performance on things as a whole. The models use the strengths of both methods and thus, its accuracy is as high as 90 percent and has better robustness and reliability. Nevertheless, with such improvements, there are still a number of problems. Problems like the lack of high-quality datasets, differences in environmental conditions (lighting, background, image quality), and complexity of real life situation have sustained their influence on the system performance. Solutions of these issues should be considered in future researches with more powerful, flexible and real-time systems, which can work under various agricultural conditions. Moreover, when combined with other new technologies, including the Internet of Things (IoT) and mobile applications, AI has much more focused prospects of practical implementation. With these types of systems, farmers are able to keep track of the health of crop in real time, take appropriate action as early as possible and it is such systems that will allow farmers to maximize their productivity and guarantee that there is food security.

REFERENCES

[1] Gonzalez, R. C., & Woods, R. E. (2008). Digital Image Processing (3rd ed.). Pearson.

[2] Canny, J. (1986). “A Computational Approach to Edge Detection.” IEEE Transactions on Pattern Analysis and Machine Intelligence, 8(6), 679–698.

[3] Otsu, N. (1979). “A Threshold Selection Method from Gray-Level Histograms.” IEEE Transactions on Systems, Man, and Cybernetics, 9(1), 62–66.

[4] Haralick, R. M., Shanmugam, K., & Dinstein, I. (1973). “Textural Features for Image Classification.” IEEE Transactions on Systems, Man, and Cybernetics, SMC-3(6), 610–621.

[5] Duda, R. O., Hart, P. E., & Stork, D. G. (2001). Pattern Classification (2nd ed.). Wiley.
[6] Cortes, C., & Vapnik, V. (1995). "Support-Vector Networks." Machine Learning, 20(3), 273–297.
[7] Cover, T., & Hart, P. (1967). "Nearest Neighbor Pattern Classification." IEEE Transactions on Information Theory, 13(1), 21–27.
[8] Quinlan, J. R. (1986). "Induction of Decision Trees." Machine Learning, 1(1), 81–106.
[9] Bishop, C. M. (2006). Pattern Recognition and Machine Learning. Springer.
[10] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). "ImageNet Classification with Deep Convolutional Neural Networks." Advances in Neural Information Processing Systems (NIPS).
[11] Simonyan, K., & Zisserman, A. (2015). "Very Deep Convolutional Networks for Large-Scale Image Recognition." International Conference on Learning Representations (ICLR).
[12] LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). "Gradient-Based Learning Applied to Document Recognition." Proceedings of the IEEE, 86(11), 2278–2324.
[13] Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.
[14] Szeliski, R. (2010). Computer Vision: Algorithms and Applications. Springer.
[15] Zhang, D., & Lu, G. (2004). "Review of Shape Representation and Description Techniques." Pattern Recognition, 37(1), 1–19.