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Fruit Disease Detection and Classification using Machine Learning and Deep Learning Techniques

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Abstract: Agriculture has a substantial role in the Indian economy within the context of India. This is the primary and essential source of income for a significant portion of the human population. Therefore, it is important to enhance the output of fruits. Fruit diseases have a negative impact on the quality and overall condition of fruits. The primary cause of fruit illnesses is mostly attributed to fungal and bacterial pathogens. The timely identification of fruit diseases serves as a means to forecast and mitigate the occurrence of such diseases, hence resulting in cost savings for agricultural practitioners. The identification of an optimal approach for fruit disease detection is used as a proactive measure to mitigate the impact of fruit diseases during their first phases. Certain researchers have undertaken the task of developing a fruit disease identification system with the aim of safeguarding farmers' investments. The primary aim of this study is to conduct a comparative analysis of a deep learning classification approach in the context of fruit disease detection. This research we proposed an fruit disease detection and classification using hybrid machine learning and deep learning techniques. The various feature extraction and selection technique are utilized and ML and DL classification algorithms are applied on heterogeneous fruit dataset. In extensive experimental analysis the proposed hybrid CNN achieves highest 97.10 accuracy for all fruit image dataset.

Keywords: *Fruit Disease Detection, Feature extraction, Feature selection, Papaya fruit, Deep Learning Techniques, Classification*

1. Introduction

Agriculture is a crucial factor in the economic development and overall progress of nations around the world [1]. The transportation of agricultural commodities throughout different regions of the world is constantly confronted with a multitude of significant challenges. In order to enhance their productivity, efficiency, and profitability, contemporary farmers need access to decision-making tools and improvements in automation that may facilitate the seamless integration of their commodities, talents, and services [2]. The concept of "smart farming" may be encapsulated by this expression. The objective of enhancing fruit yield is to augment the overall volume of fruit production, hence facilitating the advancement of the agricultural economy. Agriculture assumes a crucial role in fulfilling a significant function as a primary catalyst for economic expansion, employment, and the import-export sectors. The significance of this function is paramount for the whole economy. Ensuring the enduring viability of fruit cultivation with regards to disease control [3, 4] is crucial for augmenting fruit yield on agricultural land.

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The cultivation methods used for fruits, such as apples, oranges, grapefruits, pomegranates, and plums, are significantly influenced by the presence of minerals and nutrients inside them. Fruits serve as a very beneficial and valuable reservoir of vital minerals, including but not limited to magnesium, copper, phosphorus, calcium, potassium, and nitrogen. Iron is a mineral that can also be present in various types of fruit. Insufficient availability of critical nutrients has a substantial impact on the development, production, and quality of fruits. Over the span of a single year, the cold chain infrastructure incurs a wastage rate of around 16 for the fruits it transports. It is important to exercise cautionary measures in order to promptly identify the onset of the ailment, so enabling the implementation of appropriate interventions to safeguard the fruits from contamination. By using this measure, it would be possible to effectively prevent the transmission of the disease to other varieties of fruit and limit its potential for global dissemination. Several diseases may significantly reduce fruit yield, including as canker, anthrax, black spot, rot, and thread blight. Additional illnesses that might be seen in this context include black spot and rot. In recent years, the agricultural business has not included agricultural automation technology in the execution of harvesting, trimming, and spraying activities. The timely identification of fruit diseases and accurate forecasting of the onset of diseases in relation to fruit are crucial factors in promoting optimal fruit production [11, 16].

Advancements in cold storage and shipping have facilitated the global distribution of a wide variety of fruits, a trend that is expected to continue in the foreseeable future. There is now a pressing need to maintain the utmost degree of export efficiency, mostly accomplished via the use of visual inspection conducted by proficient experts. The typical method for identifying and categorizing illnesses involves visually examining fruit without the use of any magnifying instruments, performed by those who has knowledge about the specific ailment being investigated. The task at hand presents significant challenges due to the remote geographical locations of the farms, which in turn incurs substantial costs.

In many regions of less developed nations around the globe, the use of expert consultation might prove to be prohibitively costly and time-consuming, mostly owing to the remote areas where these services are available. This phenomenon may arise due to the considerable cost associated with traveling. Automated detection of fruit disorders is necessary in order to promptly detect signs of diseases as they manifest throughout the fruit's developmental stages [19]. Upon harvesting, it is likely that the presence of diseases inside the fruit might result in substantial losses, including both quantitative and qualitative aspects. In order to mitigate potential financial losses in the next year, it is important to possess a comprehensive understanding of the observed phenomena. Moreover, there exists a potential for the dissemination of an infection to adjacent regions inside the tree, leading to the contamination of its foliage, appendages, and trunk [6]. Apple scab, apple rot, and apple blotch represent a limited selection of prevalent diseases that possess the capacity to inflict significant damage upon apple orchards. Scaly patches on apples, often referred to as scabs, have a potential dark coloration [4]. Infections caused by apple rot result in the development of circular brown patches that have a little depression, maybe surrounded by a red halo. These patches may be seen at various locations on the apple. The illness referred to as apple blotch is caused by fungi, resulting in the manifestation of discolored, uneven, or lobed borders on the exocarp of the fruit [24, 25]. Apple blotch is a plant disease that is attributed to the fungal pathogen known as scabies. Within the industry, computer vision is being used to conduct visual inspections on fruits. This process has been automated to assess both the size and color of the fruits. Nevertheless, the task of detecting flaws remains challenging due to inherent variations in the natural pigmentation of fruit skins across various species, the extensive diversity of imperfection types, and the consistent presence of either a stem or a calyx. It is important to systematically assess the overall condition of a fruit and diligently examine for any signs of potential inside ailments. Through the use of appropriate management protocols, such as the utilization of fungicides, insecticides, and other chemically-based therapies, individuals may enhance their ability to regulate illnesses, hence augmenting the effectiveness of the therapeutic intervention. A diverse range of methodologies may be used (22, 23) to augment the efficacy of plant disease preventive and control measures. Techniques such as spectroscopy and imaging provide two prominent instances of the aforementioned methods.

Farmers consistently endeavor to discover novel approaches to minimize labor requirements while maintaining equivalent levels of production. The increasing commercialization of the agriculture industry is the underlying reason behind this phenomenon. The consideration of incorporating autonomous harvesting equipment is essential due to its potential to significantly reduce the overall cost associated with the activity. The primary use of fruit detection technology is within the realm of the harvesting industry, particularly in the domain where robotic systems have a dominant position. Nevertheless, it is possible to modify the approach to adapt it for other purposes, such as the identification of diseases, the evaluation of maturity, the tracking of tree yields, and similar procedures that have conceptual similarities [27].

Farmers use technological tools to access and gather data from credible agricultural sources, so attaining remarkable levels of accomplishment in their farming endeavors and generating substantial financial gains. The use of these strategies has the potential to provide a more advantageous expansion in terms of financial gains. The identification of plant ailments, fruit disorders, and insect infestations may be effectively achieved via the use of precision agricultural techniques. Furthermore, it facilitates farmers in accessing suitable and economically viable information and control strategies due to advancements and dissemination across various fields, enabling it to effectively support farmers in delivering sufficient and cost-efficient information and control methodologies. The two main factors leading to significant economic losses for farmers are inadequate fruit production and the propagation of diseases that affect fruit. Rapid and precise detection of fruit diseases is crucial to mitigate disease transmission and minimize fruit damage [14]. In forthcoming times, fruit cultivators equipped with advanced instruments and methodologies will possess the capability to grow and protect greater quantities of fruit. This enhanced capacity will facilitate the optimization of their financial resources, resulting in improved efficiency. Hence, it is essential to ascertain the specific ailment that is afflicting the fruit [2]. This comprehensive article provides a detailed examination of several methods used for the diagnosis of fruit infections, along with an analysis of their advantages and limitations. The author furthermore presents a comprehensive analysis of the advantages and disadvantages associated with each technique.

2. Literature Survey

The proposed model by Khattak et al. [1] was referred to as Convolutional Neural Networks (CNNs), and a comprehensive approach was used to accomplish the objective. The stated purpose of the CNN model is to discern between citrus leaves and fruits that exhibit signs of excellent health and those that display typical citrus ailments, including black spot, canker, blister, greening, or Melanose. The CNN architecture that has been created utilizes the integration of many layers to extract complementary characteristics. The CNN method was assessed against many advanced DL algorithms on both the Citrus and PlantVillage datasets. Based on the findings of the conducted research, it can be concluded that the CNN Model exhibits superiority over its rivals across several measured criteria. The CNN Model has significance as a decision support tool for citrus growers in identifying diseases that negatively impact the fruit or leaf, according to its shown accuracy of 94 in testing.

Muhammad Zia Ur Rehman et al. (2) proposed a novel approach for the categorization of citrus diseases, which is based on deep learning (DL). During the course of our inquiry, we used two distinct deep learning algorithms, each of which had undergone previous training. The use of image enhancement techniques is undertaken to expand the breadth of the previously utilized citrus dataset. Furthermore, the use of a hybrid stretching technique has been employed to enhance the overall visual quality of the photos. Furthermore, the use of transfer learning enables the retraining of pre-existing models, while feature fusion facilitates the expansion of the feature set. Both of these techniques are used in order to enhance the performance of the models. The use of a meta-heuristic method called the Whale Optimization approach (WOA) optimizes the combined feature set to achieve optimal performance. Citrus fruits exhibit vulnerability to a total of six distinct diseases, each of which may be categorized based on one of the specified attributes. The suggested technique has a classification accuracy rate of 95.7, surpassing the performance of other recently established systems.

The scholarly publication authored by Saini, A.K. et al. (201X) provides a comprehensive examination of the various methodologies used for the diagnosis and categorization of diseases affecting the foliage of citrus trees. Furthermore, this paper presents a full taxonomy of diseases that inflict harm onto the leaf tissue of citrus fruits. This study also includes an investigation into the automated identification and classification of medical conditions. Multiple diverse approaches, including preprocessing, classification, feature extraction, and feature aggregation, are currently being investigated in this study. Dubey et al. (2014) proposed a novel strategy for the identification of fruit illnesses, which was later validated by empirical investigation. The proposed method for image processing comprises several key stages. Firstly, a K-Means clustering method is employed to segment the defects in the image. Secondly, state-of-the-art features are extracted from the segmented image. Finally, a Multi-class support vector machine (SVM) is utilized to classify the images into different classes. The three types of apple illnesses, namely scab, blotch, and rot, were considered and assessed as part of the laboratory case involving apple diseases. The research used apple diseases as a model. The trial results demonstrate that the given technique effectively facilitates the precise diagnosis and automated detection of fruit diseases, hence offering substantial help in this domain. By using the provided methodology, it is feasible to get an accurate categorization of up to 93 of the queried objects. The individual in question is identified as Han, L. In a pioneering study, the researchers and their collaborators [5] have devised a unique method that use computer vision to autonomously detect agricultural diseases. The categorization of watersheds within this framework is governed by markers, while the evaluation and classification of features are conducted via the use of superpixels. The results of the research suggest that the proposed technique demonstrates efficacy in the detection and assessment of crop diseases, as well as the determination of their severity, all while maintaining a high processing speed.

Metin et al. [6] successfully produced an enhanced iteration of their Faster R-CNN framework by modifying the parameter values inside a CNN framework. The paper also presents a Faster R-CNN architecture with the aim of automating the detection of leaf spot infections in sugar beets. A total of 155 photographs were used in the training and testing of the approach developed for the identification of sickness severity using imaging-based systems with specialized knowledge. The findings from the conducted tests indicate that the technique exhibited a commendable total accurate classification rate of 95.48 percent, thereby substantiating its effectiveness. Furthermore, the shown technique provided evidence that modifying the convolutional neural network (CNN) parameters based on the image characteristics and the specific areas requiring detection might improve the effectiveness of the Faster R-CNN framework. This assertion is substantiated by the provision of the procedure. In contrast to the existing methodologies, the proposed strategy yielded superior outcomes for the key variables. Therefore, it is plausible that the use of this technique might potentially decrease the duration required for assessing the extent of the sugar beet leaf spot disease in the primary cultivation areas. Furthermore, it is anticipated that the proposed methodology would result in a reduction in the temporal resources required for the determination of the extent of the ailment and its progression.

Lorente et al. (7) investigated the use of reflectance spectroscopy within the visible and near infrared (NIR) spectra to autonomously identify deteriorated citrus fruit caused by the Penicillium digitatum fungus. The present study investigates the reflectance spectrum of sound and dissolving surface sections of mandarins cv. The spectral areas used for obtaining data on 'Clemenvilla' were divided into two ranges: 650–1050 nm, which encompasses the visible and near-infrared (NIR) wavelengths, and 1000–1700 nm, which alone covers the NIR range. The following are illustrative instances of spectral ranges. Significant discrepancies were seen in the spectra of both spectrum regions when comparing the sound and disintegrating skin. Principal component analysis (PCA), factor analysis, and Sammon mapping are three manifold learning techniques that were used to convert high-dimensional spectrum data into visually interpretable representations of lower dimensionality that retain essential information. These strategies were used to achieve this objective. A supervised classifier using linear discriminant analysis utilizes low-dimensional representations of data as feature vectors to distinguish between healthy skin and deteriorating skin. The use of NIR spectra analysis yielded the most precise outcomes in categorization, achieving a classification accuracy of 97.8. Furthermore, the well-classified specimens, whether they were in good condition or deteriorating, achieved accuracy rates of 100 and 94 respectively. As a result of these findings, contemporary commercial citrus fruit sorting systems are now equipped with the capability to use reflectance spectroscopy as a means of ascertaining the presence or absence of rot in citrus fruit.

Jahanbakhshi et al. (2018) used an enhanced variant of the Convolutional Neural Network (CNN) approach to effectively identify defects in sour lemon fruit, evaluate the severity of these issues, and devise a more efficient system. To identify potential inaccuracies, pictures of sour lemons were first categorized into two groups: those exhibiting signs of good health and those displaying indications of harm. Following the first processing stage, the images underwent classification using an enhanced Convolutional Neural Network (CNN) approach. The efficacy of CNN was improved by the use of data augmentation and stochastic pooling techniques. To evaluate the provided model in relation to established methodologies, feature extraction techniques and classification methods such as k-nearest neighbor (KNN), artificial neural network (ANN), fuzzy, support vector machine (SVM), and decision tree (DT) were used. The veracity of the CNN was verified to be 100. Hence, the utilization of CNN (Convolutional Neural Networks) and image processing techniques plays a significant role in mitigating waste and facilitating the advancement of sour lemon grading practices.

Qimei Wang et al. [9] used deep convolutional neural networks (CNNs) and object recognition algorithms to detect tomato diseases. The identification of tomato infections is accomplished by the use of Faster R-CNN, while the detection and segmentation of the affected areas of the tomato are performed using Mask R-CNN. To ascertain the optimal approach for identifying tomato illnesses, researchers use four deep Convolutional Neural Networks (CNNs) in conjunction with two item recognition algorithms. When carrying out investigations, data obtained from the Internet is often divided into three distinct segments: training data, validation data, and test sets. The suggested techniques possess the capability to efficiently and precisely discriminate among 11 distinct types of tomato diseases, while also distinguishing the geographical locations and morphological characteristics associated with each disease.

In a study conducted by Nasir et al. (2010), a Deep Neural Network (DNN) using contour features was used to classify various types of fruits and ailments. The VGG19 deep learning classifier was subjected to fine-tuning and pretraining using a dataset consisting of plant images. This process resulted in the effective extraction of meaningful characteristics from the dataset. Subsequently, the pyramid histogram of oriented gradient contour features was restored, followed by the integration of said data with the deep features using a serial-based technique. In the process of fusion, extraneous attributes were included, followed by the use of a "relevance-based" optimization approach to choose the most pertinent characteristics from the fused vector, enabling a definite classification. The technique that was advised demonstrated superior performance compared to previous approaches, with an accuracy rate of 99.6 when using several classification algorithms.

The study conducted by Ahmad et al. (2011) introduces a convolutional neural network (CNN) approach for detecting illnesses in plum. Their research demonstrates the practicality of this technique in real-world scenarios, including situations where computational resources are constrained. In contrast to datasets that are readily accessible to the public, the pictures used in this investigation were captured in situ, with meticulous attention paid to factors such as geographical context, dimensions, alignment, and other ecological factors. The implementation of substantial data enhancements led to an expansion of the dataset, hence posing challenges in effectively conducting training activities. Recent research has shown that scale-sensitive algorithms, like as Inception, exhibit superior performance when applied to challenging datasets that include significant improvements in data quality. The performance of Inception-v3 on devices with limited resources was notably improved with the use of parameter quantization. With the use of the most precise technique now accessible, mobile devices demonstrated a capability to discern between healthy and unhealthy leaves and fruit, achieving a commendable accuracy rate of 92.

The identification of guava plant species is performed by Almetwally M. Mostafa et al. [12] by the use of color-histogram equalization and unsharp masking techniques in combination with a deep convolutional neural network. A selection of nine distinct viewpoints, representing a fraction of the whole 360-degree range, were used to augment the visual representation of the plant images. The aforementioned enhanced data were gathered using modern categorization networks. The prescribed approach started with the process of standardizing and preparing the data. The experimental assessment utilizes a locally acquired dataset on guava disease in Pakistan. The suggested investigation employs AlexNet, GoogLeNet, ResNet-50, and ResNet-101 neural networks to discern several species of guava plants. The ResNet-101 model achieved a classification accuracy of 97.74, surpassing the accuracy of other classifiers.

The author's name is Williams, H.A. In a study conducted by et al. [13], a multi-arm kiwifruit harvester robot was developed and evaluated specifically for use in pergola-style plants. The safe collection of kiwifruit necessitates the use of four purpose-built robotic arms, each with a distinct end effector. Recent advancements in deep neural networks (DNNs) and stereo matching techniques have facilitated the detection and localization of kiwifruit using vision technology, even in the presence of natural lighting conditions. The harvesting method involves the use of a unique adaptive fruit scheduling technology to order the four arms. The efficacy of the harvester was evaluated in an industrial orchard, whereby it was observed that the device successfully harvested around 51 of the total kiwi fruit within a time frame of 5.5 seconds per fruit.

Santos, T.T. has shown the contemporary convolutional neural networks (CNNs). According to the study conducted by et al. [14], it has been shown that there exists the capability to identify, divide, and track wine grape clusters, even in cases where these clusters exhibit variations in terms of their form, color, size, and compaction. In the experimental dataset consisting of 408 grape clusters captured by photography in a vineyard using a trellis-system, a classification F1 score of 0.91 was achieved. This facilitates more precise assessments of fruit dimensions and morphology. A publicly available dataset of 300 annotated grape clusters, together with a unique segmentation algorithm specifically designed for complicated objects in actual photographs, has been provided. The pipeline facilitates the annotation, training, evaluation, and monitoring of agricultural patterns shown in images across many crops and production systems. The technology has the capability to manufacture sensor components suitable for agricultural and environmental purposes.

The Mask Region Convolutional Neural Network (Mask-RCNN) was created by Yu et al. (2015) with the objective of enhancing the efficacy of computer vision in the task of fruit detection for use in a strawberry harvester machinery [15]. The decision was made to use Resnet50 as the foundational framework for the network, while the Feature Pyramid Network (FPN) architecture was selected to facilitate the extraction of features from the network. The Region Proposal Network (RPN) underwent thorough training during its entire duration to enable the generation of region proposals for each attribute map. Following the completion of creating mask pictures of ripe fruits using Mask R-CNN, a technique for image localization in strawberry harvesting locations was implemented. The findings from the analysis of 100 test pictures demonstrated an average accuracy rate of 95, a recall rate of 95, and a mean intersection over union score of 89.85 for fruit identification. The findings were derived from an average accuracy rate of 95 and a recall rate of 95. The findings from the analysis of 573 locations designated for ripe fruit harvesting revealed that the average discrepancy was 1.2 millimeters lower than the initially estimated value. This was shown by the observation that the average error was lower than the anticipated value.

Deep Orange, DL is a system that was introduced by Ganesh, P. et al. [16]. It utilizes the Mask R-CNN instance segmentation technology, which is currently considered the most powerful. The system is designed to detect and segment fruits at a pixel level. To achieve this, it incorporates information from various sources, including RGB and HSV photographs of the scene. The architectural design is assessed by analyzing photographs taken in their authentic environment, namely an orange grove located in the state of Florida. The experiment used images in both the RGB color space and the RGB+HSV color space to assess the effectiveness of the algorithm. The first use of just RGB data resulted in an accuracy of 0.89. However, the incorporation of HSV data yielded an enhanced accuracy of 0.9, hence indicating an improvement over the prior accuracy of 0.89. The F1 score attainable in the RGB+HSV color space is around 0.89.

The author's name is Liu, Z. In their study, et al. [17] used the commonly utilized Faster R-CNN model VGG16 in conjunction with transfer learning to achieve the objective of kiwifruit identification. This was accomplished by analyzing images obtained from two unique techniques, namely RGB and NIR photos. The aforementioned action was undertaken with the purpose of achieving the objective of kiwifruit identification. The acquisition of NIR and RGB images of kiwifruit canopies from a bottom perspective was facilitated by using a Kinect v2 device. The composite image consists of a single-channel near infrared image and three-channel red, green, and blue images, arranged side by side to create a six-channel picture. To get a picture with six channels, it is necessary to adjust the parameters of the input region of the VGG16 model. Image fusion and feature fusion are two often used fusion techniques for feature acquisition. The input layer of the network used a software program known as Image-Fusion to blend the Red-Green-Blue (RGB) and Near-Infrared (NIR) images. Following the completion of training the updated networks utilizing reverse propagation and stochastic gradient descent methods, a comparison was made with the initially constructed VGG16 networks that just received RGB and NIR picture input. The purpose of this comparison was to ascertain the network that exhibited superiority. Based on the results, it was observed that the average precision of the original VGG16 model using RGB and NIR image inputs was 88.4 and 89.2 respectively. In contrast, the average precision of the 6-channel VGG16 model employing the Feature-Fusion technique reached 90.5. Moreover, the 6-channel VGG16 model utilizing the Image-Fusion technique achieved the highest attainable average precision of 90. Additionally, the fastest detection speed was recorded at 0.134 seconds per picture.

In this study, Ge et al. (2018) propose a methodology that may be used for the purposes of strawberry identification, instance segmentation, and improved localization. The used approach utilizes a Deep Convolutional Neural Network (DCNN). The fundamental methodology used in this study is on deep learning. The DCNN algorithm identifies four distinct categories, with three corresponding to different stages of ripeness seen in strawberries, and the fourth category specifically assigned to strawberries exhibiting abnormal morphology. According to the findings of the study, ripe strawberries can be distinguished from the other four groups with little effort. Subsequently, the use of bounding box refinement was employed with the aim of enhancing the precision of the localization outcomes. The identification of obstructed fruits and the calculation of actual fruit sizes were achieved by the use of boundaries in this approach. A comparable method of refinement, which takes into account the rigidity of the mask's form, was suggested to uncover the concealed boundary of the fruit. Additionally, the width to height ratio (WHR) of the generated masks was used to identify obstructions. This facilitated the discernment of the obscured boundary of the fruit. During the third step, the obscured side was refined by compensating for the occluded area using the median width-to-height ratio (WHR) of the strawberries that were not obstructed. This additional step increases the cumulative number of steps to three. The experiment used the 'Lusa' strawberry variety to test the efficacy of the refining technique, demonstrating its capability to accurately detect and restore the true proportions of the item. The comparison test reveals that the degree of overlap between the raw identified data and the ground truth is 0.68, while the bounding box intersection between the enhanced data and the ground truth is 0.87. Based on the available data, it can be inferred that the modified methodology has an enhanced capacity for accurately identifying various types of fruits.

The authors, Altaheri, H. et al., The computer vision technique proposed by et al. [19] presents an efficient and effective approach for accurately determining the age of fruit harvester robots. The system consists of three discrete classification algorithms used for real-time classification of date fruit photos, based on the kind of date fruit, its maturity level, and the determination of when to harvest it. When categorizing photos of date fruit, these aspects are considered. Deep Convolutional Neural Networks (DCNNs) are used in the classification models, with the incorporation of Transfer Learning (TL) and the process of fine-tuning on previously established methodologies. A comprehensive compilation of images depicting various clusters of date fruits inside an orchard has been assembled with the purpose of constructing a reliable vision system from its inception. The present compilation has a total of 8000 pictures depicting five distinct categories of dates at different stages of pre-maturity and maturity. The dataset exhibits a significant degree of heterogeneity, which may be attributed to the inherent difficulties encountered in the date orchard environment. The problems include a range of factors, such as the need to adapt to varying perspectives, dimensions, and lighting circumstances, and the handling of date clusters that are packaged inside sacks. The accuracy rates for the proposed date fruit classification algorithms were found to be 99, 97, and 98.5 for the categorization tasks of type, ripeness, and harvesting choice, respectively. The corresponding durations for these classifications were 20.6, 20.7, and 36 milliseconds.

The authors Zapotezny-Anderson, P., et al. [20] provide Deep-3DMTS as a methodology aimed at developing a unified viewpoint for 3DMTS. The use of a convolutional neural network (CNN) is employed by this approach. Following the development of a unique methodology, we proceeded to subject it to rigorous testing in a simulation in order to evaluate its performance relative to the usual 3DMTS technique. Previous studies have shown that the Deep-3DMTS technique has a level of efficacy similar to that of the regular 3DMTS baseline approach in directing the end effector of an autonomous robotic arm to enhance the visibility of a concealed fruit. The proposed system demonstrates an end effector's final position that exhibits a proximity of 11.4 millimeters to the baseline. Additionally, the image showcases a significant enlargement in fruit size, with a magnification factor of 17.8 relative to the baseline value of 16.8, on average.

The author of the text is Lin, G. The authors in the study conducted by et al. [21] developed a method for fruit identification and posture estimation. Their objective was to enable autonomous decision-making without collisions utilizing an affordable red-green-blue-depth (RGB-D) detector. The objective is to conduct fruit selections while minimizing any potential harm to the produce. During the first phase of the approach, a state-of-the-art convolutional neural network (CNN) is used to perform segmentation on the RGB picture. This segmentation process aims to provide a binary mapping that distinguishes the fruit and branches within the image. This first stage marks the commencement of the procedure. Once the fruit binary mapping and the RGB-D depth picture have been used, the subsequent procedure involves the application of Euclidean segmentation. This process aims to organize the focus point cloud into distinct entities representing individual fruits. In the succeeding phase, a novel technique is devised to detect and classify various segments of a line inside a three-dimensional space, with the objective of reconstructing fragmented branches. This task is completed in anticipation of the subsequent phase. In summary, the 3D orientation of the fruit is estimated by using data on the position of the fruit's core and the nearest segment of the branch. A dataset was collected from an orchard located in an outdoor setting in order to assess the effectiveness of the suggested approach. The results of the quantitative testing revealed that the guava identification process exhibited an accuracy rate of 0.98 and a recall rate of 0.94. The study revealed that the 3D posture inaccuracy measured 23.4 degrees and 14.1 degrees, respectively. Additionally, the average time required for implementing the task on each fruit was found to be 0.5 seconds. The findings provide empirical evidence that a bot specifically designed for guava collection can proficiently implement the stated methodology.

The individual in question is named Orchi H. The authors in the study conducted by et al. [22] provide a contemporary evaluation of the research conducted in the last decade about the identification of diseases in various crop species. This is achieved by the use of methodologies such as machine learning (ML), deep learning (DL), image processing techniques, the Internet of Things (IoT), and hyperspectral analysis of images. This research effort was conducted with the aim of identifying illnesses in a diverse range of crops. However, much study has been conducted to examine the similarities and differences across different approaches used for diagnosing plant diseases. Furthermore, this article examines the manifold obstacles that need resolution, along with potential remedies to address these matters and their corresponding apprehensions. Subsequently, a range of recommendations for effectively tackling and surmounting these obstacles are presented. In conclusion, the findings of this study provide a promising outlook for further investigation, which has significant promise in becoming a valuable and prominent resource for scientists engaged in the area of crop disease detection.

The approach proposed by Abbas et al. (23) used deep learning techniques for the purpose of detecting diseases that impact tomato plants. The approach utilizes the Conditional Generative Adversarial Network (C-GAN) to produce synthetic images of the leaf surfaces of tomato plants. A DenseNet121 model is implemented on both simulated and real pictures using transfer learning (TL) methodology to accurately categorize images of tomato leaf diseases into 10 distinct classes. The categorization of these entities is established on the basis of the visual attributes shown in the photographs. The model indicated above has been created and thoroughly validated using the dataset supplied by PlantVillage, which is accessible to the general public. The technique that was advised exhibited success rates of 99.5, 98.6, and 97.1 in the classification of tomato leaf photographs into five categories, seven categories, and ten classes, respectively. The provided approach demonstrates its superiority over the already utilized methods in the given circumstance.

The user's text is too short to be rewritten academically. In their work, Wang et al. (24) use apple, peach, orange, and pear as the components of their investigation. They propose a model that utilizes Mask R-CNN to accurately identify disease spots on the external surface of these fruits. The occurrence of these patches is often attributed to either a fungal or viral etiology. Once the collecting robot successfully locates and identifies the fruit, this particular model proceeds to conduct a precise evaluation of any potential imperfections present on the fruit's outer peel. The current method for detecting fruit surface illnesses is characterized by a lack of precision, slow processing speed, and a significant load in terms of quality categorization. The feature pyramid framework (FPN) used by Mask R-CNN has been modified to include a horizontal connecting route in order to enhance the fusion of high-level and low-level features. The modification was implemented with the aim of enhancing the integration of high-level and low-level characteristics. The enhanced Mask R-CNN methodology achieves a detection rate of 95 for all four distinct types of fruit surface blemishes. Additionally, the use of a GPU results in an increased detection rate of 2.6 frames per second. The proposed method exhibits superior speed compared to both the Fast R-CNN and SSD approaches, while also demonstrating exceptional detection efficiency and robustness.

The user's text is too short to be rewritten in an academic manner. The user's text is too short to be rewritten in an academic manner. Please provide a A diverse array of color, texture, and form feature combinations were used in the creation of the artwork in this piece. N. suggested an approach for image processing. In their study, Ayyub et al. (25) aimed to identify and classify diseases that have the potential to impact apple fruit. The proposed methodology commences with the categorization of images, followed by the extraction of features encompassing color, appearance, and form. Subsequently, these attributes are integrated, culminating in the identification of apple diseases and the classification of apples into two categories, namely healthy or diseased, utilizing a multi-class support vector machine. The recommended technique has the potential to achieve an accuracy level of up to 96.

3. Research Methodology

Taking into account the fruit is the best way to classify the disease. Deep learning (DL) and Machine Learning (ML) methods for detection can be applied in order to determine which fruits are afflicted with the disease. There are six primary stages involved in the methodologies of deep learning. Initially photos will need to be gathered, then preprocessing, segmentation, feature extraction, and classification will take place, and finally, the type of disease will be forecasted. Figure 1 illustrates the block diagram of the generic steps for detecting fruit disease using DL classifiers

Image Acquisition: The process of acquiring images is the initial step of the system intended for identifying diseases in fruit. Photographs taken by sensors, drones, or cameras typically have the highest possible quality. The photos that were collected are in RGB format. After the creation of the color conversion framework for the RGB fruit picture, a device-independent hue conversion is then applied to the color conversion framework.

Image Pre-processing: There are a number of different ways that can be utilized in order to eliminate additional objects or noise from a picture. To clip a photograph, first crop the picture of the Fruit to obtain the area that is relevant in the image. A smoothing filter is applied whenever there is a need for smoothing. The enhancement of the image is performed in order to increase the contrast, then color conversion is used to transform pictures with RGB values into grayscale images, and finally, histogram equalization is utilized so that the intensities of the pictures are distributed evenly.

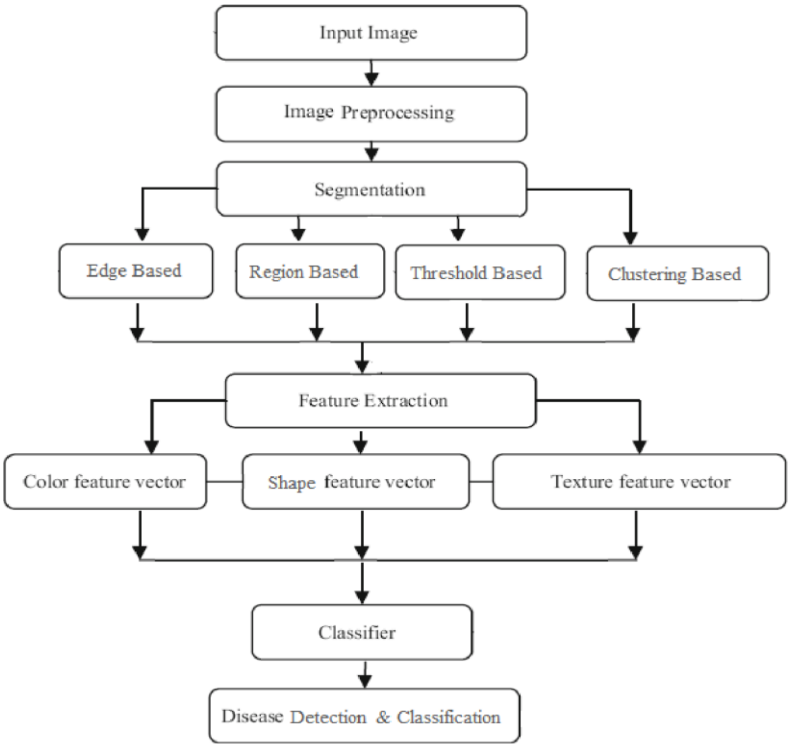

Fig 1 : Proposed system architecture for fruit disease detection and classification

Image Segmentation: The term "segmentation" refers to the process of splitting a picture into multiple components that have the same characteristics or have some similarities. Different methods, such as the otsu' method, k-mean clustering, turning RGB images into HIS models, and many others, can be utilized in the segmentation process.

Feature Extraction: Extracting Features is a technique that is utilized to assess the overall effectiveness and quality of an image by utilizing features such as color, surface texture, shape, and other similar characteristics. It is possible to extract features from a picture using a variety of methods, such as the Global Color Histogram, Color Coherence Vector, Local Binary Pattern (LBP) and Complete LBP.

Classification: The last phase in this process is classifying various fruit diseases through the use of DL techniques. There are a few different approaches to classifying things: Support Vector Machine (SVM), Multiclass SVM, Artificial Neural Network (ANN), Probabilistic Neural Network (PNN), Backbone Propagation Neural Network (BPNN), Feed forward Back propagation Neural Network (FFBPNN) etc.

4. Results and Discussions

The concluding part of the systems process involves synthesizing the findings, including the conducted tests, the acquired results, and the subsequent analysis and establishment of conclusions. The study is conducted via the implementation of several studies in order to examine the performance of the proposed algorithm. This examination is dependent on a range of characteristics, including the size of the dataset, the shape of the dataset, and the inputs provided to the algorithm. A deep learning model, often referred to as an error matrix, is a tabular representation used for visualizing the output of an application, especially in the context of supervised learning within the subject of machine learning. It specifically addresses the problem of statistical categorization. In the matrix, the columns correspond to the instances seen in a real class, while the rows correspond to the anticipated instances in a class. The nomenclature is derived from the inherent capacity of the technique to facilitate the discernment of potential confusion between two distinct groups. In the context of supervised learning, an uncertainty matrix serves as a straightforward mechanism for assessing the results. The phrase is used to characterize the outcome of an evaluation conducted on a predictive model. In the above matrix, the examples in a predicted class are represented by each column, while each row represents the classes in a class diagram. A series of four separate experiments were conducted in order to evaluate the effectiveness of the discriminant function across different formats of datasets.

The accuracy, as defined by Equation 1, is the proportion of correct forecasts relative to the total number of projections. The equation is used for the purpose of quantifying it.

$$acc = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

The equation provided in the study has been used to determine the desired accuracy, resulting in around 97.10 precision in forecasting. This level of precision surpasses that of all other approaches examined. In this investigation, the F1-score was used as an evaluative metric to compare the results of several studies. Convergent and discriminant validity are used for the assessment of the F1 score, as shown by Equation 2. In equations (3) and (4), TP represents a positive outcome, FP represents a false positive outcome, and FN represents a negative test outcome.

$$F1 = 2 \times \frac{precision \times recall}{precision + recall} \quad (2)$$

$$precision = \frac{TP}{TP+FP} \quad (3)$$

$$recall = \frac{TP}{TP+FN} \quad (4)$$

Table 1 : Comparative analysis of proposed model with various learning algorithms

Algorithm	**Accuracy**	**Recall**	**Precision**
ANN	0.90	0.87	0.93
SVM	0.88	0.84	0.93
NB	0.88	0.84	0.94
RF	0.87	0.82	0.94
Fuzzy	0.89	0.85	0.93
PNN	0.90	0.87	0.93
RNN	0.89	0.86	0.93
RNN+LSTM	0.88	0.84	0.93
CNN	0.88	0.85	0.93
FCNN	0.86	0.80	0.93
DCNN	0.88	0.85	0.93
DNN	0.89	0.87	0.93
GAN	0.89	0.87	0.93
HCNN	0.**97**	0.9**8**	0.**97**

The proposed methodology involves the use of a hybrid model that combines Convolutional Neural Networks (CNN) with the VGGNET-16 architecture and the YOLOV8 model for the purpose of segmenting pomegranate fruit. The acquired accuracy in this study is 97.10, surpassing the precision of existing Deep Learning models.

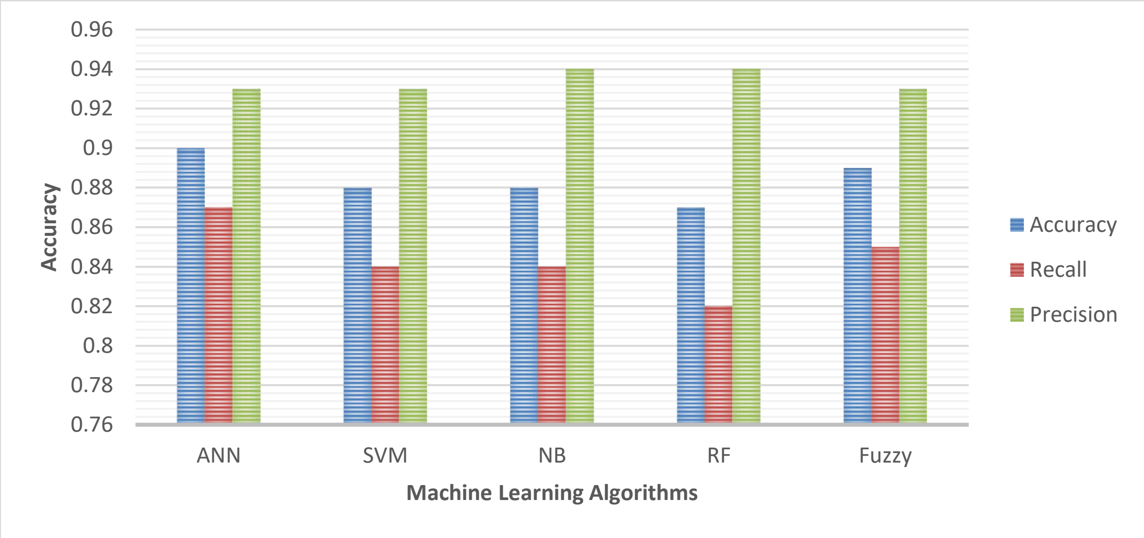

Fig 2 : classification accuracy with various machine learning algorithms for fruit disease detection and classification

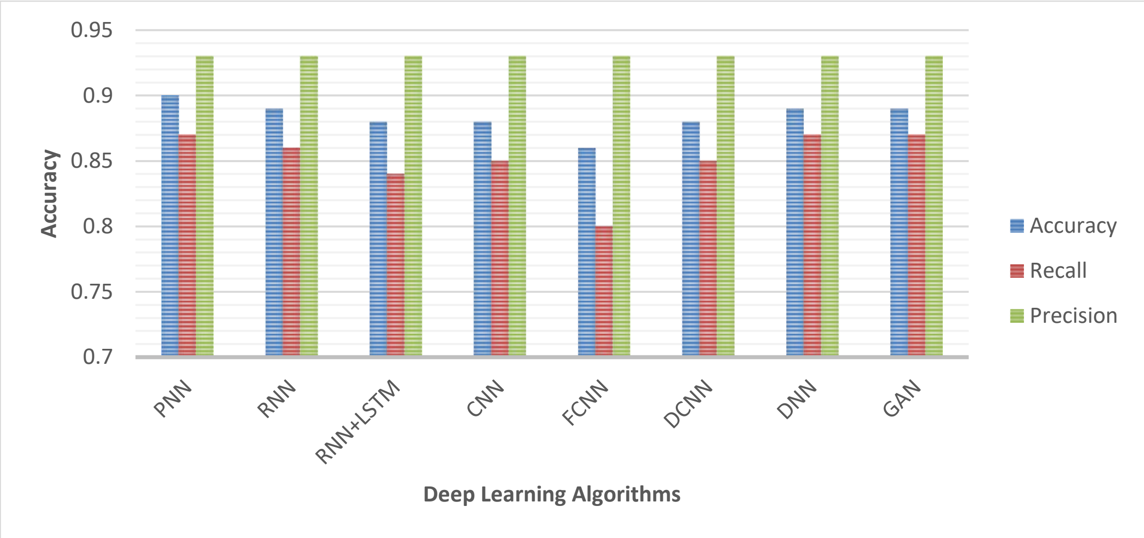

Fig 3 : classification accuracy with various deep learning algorithms for fruit disease detection and classification

Figure 2 describes an fruit disease detection using machine learning algorithms while Figure 3 demonstrates classification accuracy using various deep learning algorithms. In the context of data organization or classification, the most current approach for prediction involves the use of a training set and a test set.

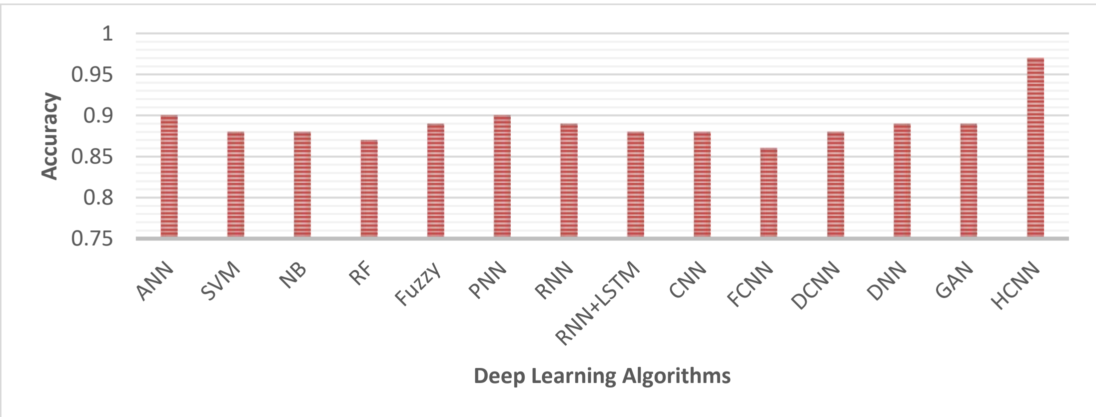

Fig 4 : comparative analysis using various machine learning and deep learning algorithms for fruit disease detection and classification

The proposed approach utilizes a hybrid model that combines Convolutional Neural Networks (CNNs) with the VGGNET-16 architecture and the YOLOV8 model for the purpose of segmenting pomegranate fruit. The acquired accuracy in this study is 97.10%, surpassing the precision of existing Deep Learning models. Figure 5 presents a comparative analysis of the classification accuracy of the suggested algorithms in relation to other established machine learning approaches. In the context of data organization or categorization, the most current approach involves the use of a training set and a test set for predictive modelling. The training package comprises input function modules and their corresponding class labels. The purpose of this learning set is to develop a classification model that effectively categorizes the incoming data into suitable template files or labels. The model is then verified by using a test set that is generated from the class labels present in the whole of the test dataset.

5. Conclusion

This study focuses on exploring several machine learning and deep learning classification methodologies for the purpose of identifying and categorizing diseases affecting fruits. A number of publications exhibit a preference for using Support Vector Machines (SVM) in conjunction with a k-means clustering approach as an alternative to conventional classification techniques. The findings indicate that the CNN Classifier has a high level of accuracy in properly diagnosing fruit diseases. In the future, it is plausible that other machine learning and deep learning classification algorithms, such as decision trees and other classifiers, might be used for the purpose of disease detection in plants. This technological advancement has the potential to greatly assist farmers by automating the diagnosis of many plant illnesses. In future work, the use of more sophisticated deep learning models, along with the optimization of model parameters, has the potential to enhance the accuracy of detection and classification while concurrently mitigating memory consumption. One potential approach to enhance the effectiveness of the analysis is to use a more extensive dataset with a greater number of species. Additionally, incorporating a wider range of fruit images, including both authentic photographs and synthetic representations, might further augment the dataset's diversity. In the future, there is a desire to transform the aforementioned system with the objective of detecting and categorizing faulty and damaged crops. The use of smart farming practices in the contemporary day would constitute a very advantageous innovation for agricultural practitioners.

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