DETECTION OF FRUIT DISEASES WITH HYBRID DWT-GLCM APPROACH

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ABSTRACT

Fruit diseases are a serious issue that is having a big global impact on yield quality and quantity. One of the reasons for financial shortfalls in the global agriculture sector is plant diseases. It is the most crucial element since it lowers the growing crops' potential and quality. Although fruits are one of the most significant sources of nutrients in plants, a wide variety of illnesses can impair the quality and growth of fruits. Brown spot, black dot, greasy spots, canker, dry rot, black spot, greening, bacterial blight, pests, peach & nectarine, etc. are only a few of the illnesses that can affect fruits. For the prediction and categorization of citrus infections, many algorithms have been looked at and put forward by analysts in the fields of artificial intelligence, machine learning, digital image processing, and deep learning.

The findings demonstrate that methods for data augmentation and pre-processing have produced encouraging findings for estimating fruit's damages.

1. INTRODUCTION

A key factor in assessing the amount to which a disease influences yield production is the disease's severity. [6] Usually, output shortfalls might be avoided with the support of a prompt and accurate diagnosis of disease severity, which is done by qualified experts by visually examining plant tissues. The rapid advancement of modernized agriculture is hampered by the high expense and ineffectiveness of human illness assessment. [7] In this study, deep learning models for fruit disease severity level automatic picture diagnosis are presented. This article discusses issues with determining the extent of illness in fruits using a multi-classification framework and a deep learning model. In the current study, the fruit samples are pre-processed using labelled image software, which entails rescaling and making bounding boxes. [8] The benefits of exhaustive search and graph-based segmentation are then combined in a method known as selective search. The disclosed DNN technique recognizes the stated illness region and severities using oranges with four severity levels (high, medium, low, and healthy) that were seen by a domain expert. [9] Transfer learning with VGGNet is utilised to build a multi-classification framework for each severity class.

1.1 Fruits Disease Symptoms

Fruit diseases are a serious issue that is having a big global impact on yield quality and quantity. [10] One of the reasons for financial shortfalls in the global agriculture sector is plant diseases. It is the most crucial element since it lowers the growing crops' potential and quality. [11] Although fruits are one of the most significant sources of nutrients in plants, a wide variety of illnesses can impair the quality and growth of fruits. Brown spot, black dot, greasy spots, canker, dry rot, black spot, greening, bacterial blight, pests, peach & nectarine, etc. [12] are only a few of the illnesses that can affect fruits. Figure 1 shows the visual symptoms of these images.

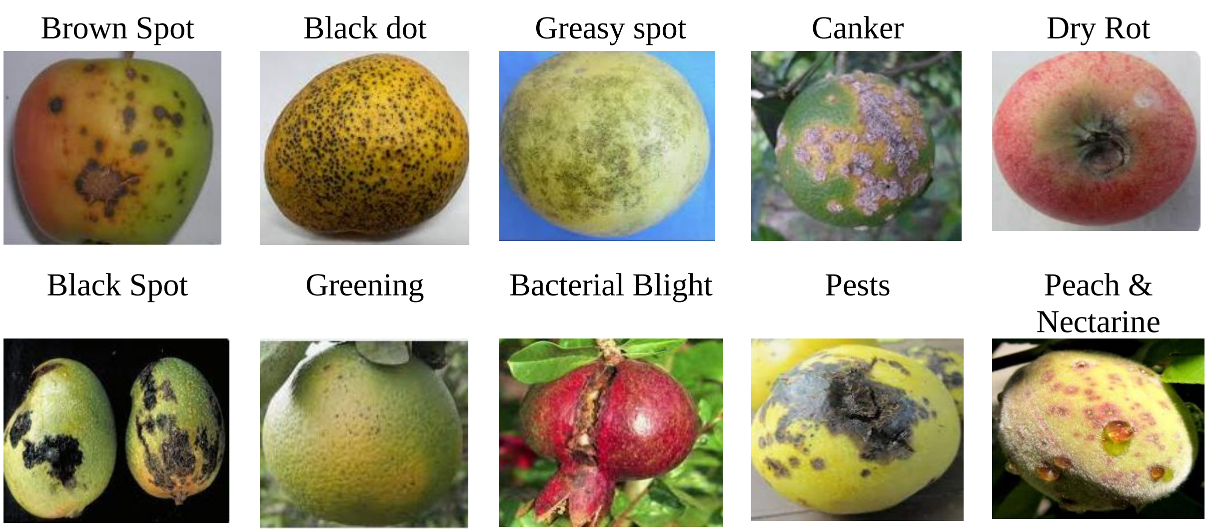

Figure 1 Visual Symptoms Of Diseases

2. LITERATURE REVIEW

Zhang et al. (2020) focused on fruit quality classification using machine learning techniques. The paper may discuss the utilization of different machine learning algorithms to classify fruits based on their quality attributes. The authors likely describe the dataset, the feature extraction process, the classification algorithms used, and the evaluation metrics employed. The paper may present experimental results and discuss the effectiveness of the machine learning techniques for fruit quality classification.

Guo et al. (2018) presented a classification approach specifically for apples based on machine learning. The paper likely describes the dataset used, the preprocessing steps, and the feature extraction techniques employed to differentiate between different apple varieties or quality levels. The authors may discuss the machine learning algorithms used for classification, the evaluation metrics used to assess the performance, and provide experimental results and analysis.

A fruit quality classification system that combines image processing methods and machine learning algorithms was suggested by Karthikeyan et al. in 2020. The use of image processing methods to extract pertinent characteristics from fruit photos, followed by the use of machine learning algorithms for classification, is likely covered in the study. The dataset utilised, the precise image processing methods applied, the machine learning algorithms used for classification, and the evaluation metrics to gauge the efficacy of the suggested methodology may all be presented by the authors.

Aramendia et al. (2020) unveiled a deep learning method for judging fruit quality. The implementation of deep learning methods, including convolutional neural networks (CNNs), for determining fruit quality is perhaps the paper's main focus. It could go through the dataset utilised, the deep learning model's architecture, the training procedure, and the evaluation metrics employed to gauge the model's effectiveness. The authors may discuss their experimental findings, contrast their strategy with current practises, and offer perceptions on the potential of deep learning for evaluating fruit quality.

3. PROPOSED METHODOLOGY

Figure 2 depicts the process model for the proposed approach. [13] Median filter and K-Means Clustering are used to improve and segment the input photos. [14] The segmented image is subsequently put through DWT. The GLCM approach is then used to extract the features. Then, to recognize and describe the potato sicknesses, the classifiers Naive Bayesian, ANN, KNN, and Multiclass SVM are utilized independently. [15] Zhang et al. (2020) proposed a fruit quality inspection method based on machine learning algorithms. The paper likely discusses the application of various machine learning techniques for fruit quality assessment. It may describe the dataset used, the preprocessing steps, the feature extraction methods, and the specific machine learning algorithms employed. The authors likely present the results of their experiments and discuss the performance of the proposed method for fruit quality inspection.

A hybrid is a combination of one or more procedures. In the proposed work, the combination of characteristics produced using the DWT and the GLCM, two different techniques, is referred to as a "hybrid." [16]

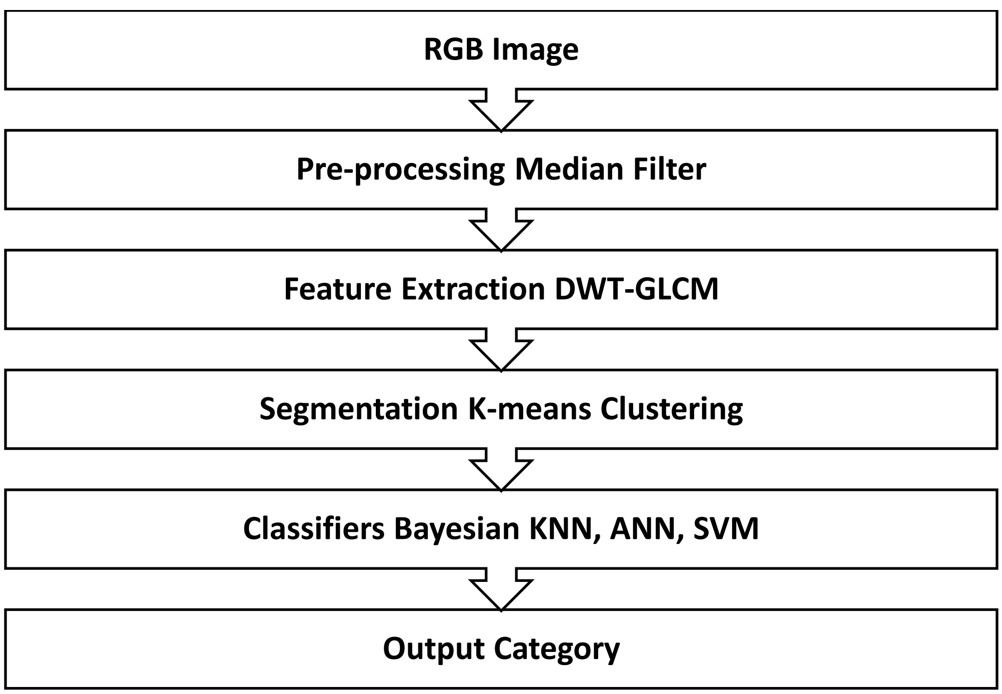

Figure 2 Flow Diagram

3.1 Image Pre-Processing:

It's a method for eliminating distracting noise in photos. This method improves the overall quality of a shot. [17] Images before preprocessing, after Grayscale conversion, and before RGB input are all shown in Figure 3. Using a median filter improves the quality of an obtained picture.[18]

RGB Image **Grayscale Image** **Pre-processing Image**

Figure 3 Input RGB and Pre-processing Image

The median filter is a nonlinear filter that helps reduce or get rid of unwanted background noise in an input picture. [19] This filter gets rid of the salt and pepper noises. Using this technique, the grey level median value of neighboring pixels is substituted for each pixel in the input picture. Using the method described below, we can determine the median. [20]

1. Pixel values are sorted in ascending order.
2. Then substitutes a median value for the pixel value.

3.2 Segmentation:

In the wake of pre-processing comes segmentation. [21] The picture is broken up into several smaller pieces called clusters, and each cluster has a similar collection of pixels. The K-Means Clustering technique is used to partition the picture in the presented approach. [22] In Figure 4, we see both the original RGB picture and the segmented version.

RGB Image **Segmentation Image**

Figure 4. Input RGB and Segmented Image

The K-Means Clustering method divides the input photos into clusters based on the similarities between them.[23] There are two stages to this procedure. To begin, we find the centers of K. Then, the walls between the various hubs are built. In the next phase, all of the cluster's nodes and their centers are taken into account. The Euclidean distance is used to find the nearest centroid. [24] The updated cluster centroid is then utilized in a recompilation of all clusters. As shown in Equations (1) and (2), the Euclidean distance between each cluster center and each data point may be precisely calculated.

$$(E.d)^2 = \min(\mu_1 - \mu_2) \sum_{i=1}^{i=n1} \sum_{j=1}^{j=n1} |X(i,j) - \mu^2| \tag{1}$$

$$\mu_k = \frac{\sum_{i=1}^{i=n} P(i) + i}{\sum_{i=1}^{i=n} P(i)} \tag{2}$$

Figure 5 shows the RGB image and the K-Means Clustering image. [25] The ill region in this image was located by the second cluster.Each cluster in the image is allocated the minimal distance.Every cluster has a defined set of member objects and their centroid positions.

RGB Image **K-means Clustering Image**

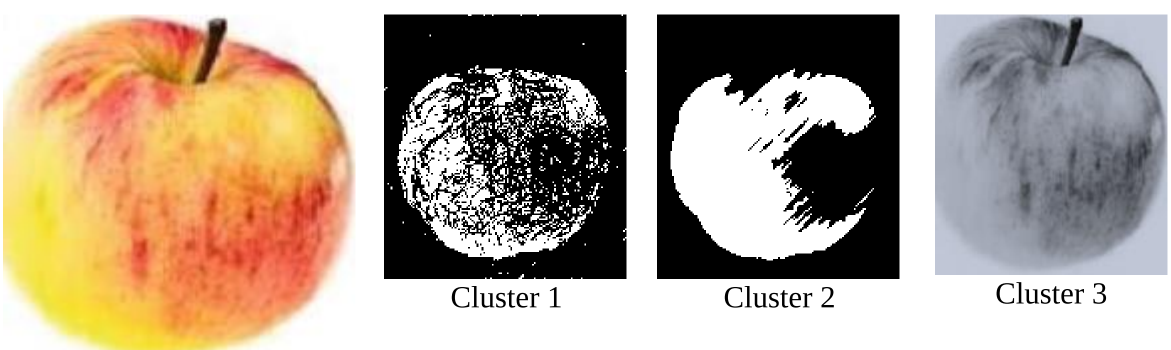

Figure 5 Input RGB and K-means cluster Image

As a result, this approach shortens the distance between the cluster item and centroid. It is an iterative segmentation model. [26]

4. RESULTS ANALYSIS

The fruits diseases employed in this study are Silver scurf, Skin spot, Dry rot, Gangrene, Pink rot/Watery wound rot, Brown spot, Black dot, Soft rot, Bacterial wilt, Soil-Borne, Tuber, etc. The Classifier employs these features to determine the disease type after retrieving the attributes of these input pictures in three different ways. The experiments are all carried out using MATLAB.

The three techniques presented in this paper are Approach 1 (SIFT Feature extraction), Approach 2 (GLCM Feature extraction), and Approach 3. (Hybrid DWT-GLCM feature extraction).A median filter is utilized in Method 1 to enhance the recorded input photographs. The image is next separated into segments using Otsu thresholding, and features are then extracted from the segmented images using Scale-invariant Feature Transform.

Contrast enhancement is applied to the input photographs that were obtained as a pre-processing step in the second approach. The image is then segmented using K-Means Clustering, and features are then produced from the segmented images using the Gray Level Co-occurrence Matrix (GLCM).

Table 1 : Accuracy results of Proposed Algorithm

Algorithm	K- Means	SVM	DWT-GLCM
Accuracy	.87	.81	.93
Precision	.83	.82	.92
Recall	.81	.78	.92
F1	.79	.73	.90

5. DISCUSSIONS

5.1 Implications of Findings

The implications of the findings were discussed, considering their relevance to fruit spoilage detection applications. The strengths and limitations of the Naive Bayesian, ANN, KNN, and SVM classifiers were summarized, highlighting their suitability for specific scenarios or requirements. The practical implications of the findings, such as the potential for automation and improved quality control in the food industry, were also discussed.

5.2 Comparative Analysis with Previous Studies

The findings of this study were compared with previous research on fruit spoilage detection using machine learning algorithms. Consensus and divergence in the results were identified, and the factors contributing to these differences were discussed. The study's contributions to the existing body of knowledge were highlighted, emphasizing its unique insights and potential advancements in fruit spoilage detection research.

5.3 Practical Considerations and Future Directions

Practical considerations for implementing fruit spoilage detection systems based on the Naive Bayesian, ANN, KNN, and SVM classifiers were discussed. Recommendations were provided for optimizing the classifiers' performance in real-world applications, considering factors such as dataset size, feature representation, and model complexity. Future research directions were suggested. The input fruits disease images are used to test the classifier. Then, the Naive Bayesian, ANN, KNN, and SVM classifiers are employed to categorize these images.The performance of each classifier is assessed by calculating evaluation metrics such as accuracy, precision, recall, F1-score, and the confusion matrix. These metrics will allow you to compare the classifiers and determine which one performs best for your specific task of categorizing fruit disease images.

6. CONCLUSION

In this study, we proposed a comprehensive investigation of fruit spoilage detection using the Naive Bayesian, ANN, KNN, and SVM classifiers. Our objective was to compare the performance of these classifiers and provide insights into their suitability for fruit spoilage detection tasks. Our findings showed that each classifier exhibited different strengths and weaknesses in fruit spoilage detection. These findings have significant implications for the development of fruit spoilage detection systems. The Naive Bayesian, ANN, KNN, and SVM classifiers can be utilized in different contexts based on their specific advantages. Implementing these classifiers can lead to improved quality control, reduced waste, and enhanced agricultural and food industry productivity.

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