

RSNT-SSAE: A HYBRID DEEP LEARNING AND SPARSE FEATURE LEARNING FRAMEWORK FOR ROBUST ORANGE FRUIT DISEASE DETECTION AND CLASSIFICATION

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ABSTRACT

Accurate and timely detection of fruit disease is essential for maintaining crop quality and minimizing economic losses in citrus production. Orange fruits are susceptible to various diseases that directly affect their surface appearance, leading to reduced market value and increased post-harvest losses. Manual inspection methods are often time-consuming, subjective, and impractical for large-scale applications. To address these challenges, this paper presents an automated framework for detecting and classifying orange fruit diseases based on deep learning and machine learning techniques. The proposed model integrates a ResNet50-based deep feature extraction approach with a Stacked Sparse Auto Encoder (SSAE) classifier, referred to as the RSNT-SSAE framework. Before classification, orange fruit images undergo Wiener filter – based noise removal to suppress image noise, followed by Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance visual contrast. Color – based segmentation using RGB thresholding is employed to isolate disease – affected regions from the fruit surface. Deep features extracted using the ResNet50 architecture are then classified using the Stacked Sparse Auto-Encoder (SSAE) model to distinguish between healthy and diseased fruit categories. Experimental evaluation conducted on a publicly available orange fruit dataset demonstrates the effectiveness of the proposed approach, achieving a classification accuracy of 98.10%. The results indicate that the RSNT – SSAE framework provides robust and reliable performance, making it a promising solution for automated orange fruit disease diagnosis and precision agriculture applications.

Keywords: *Image processing, orange fruits, Deep learning, ResNet50, CLAHE, Machine Learning.*

1. INTRODUCTION

Oranges, often regarded as one of the most valuable citrus fruits, are widely consumed across the world due to their refreshing taste, vibrant appearance, and rich nutritional profile [1]. Orange fruit is a major horticultural crop and plays a vital role in global agriculture; however, orange cultivation faces serious challenges due to the prevalence of fruit diseases that directly affect surface quality and market value. These diseases significantly reduce yield and lead to substantial economic losses for farmers and stakeholders in the citrus supply chain. With the rapid evolution of information and computer technologies, computer – aided diagnosis systems have emerged as effective tools in agricultural applications, enabling faster,

more accurate, and more consistent detection and classification of fruit diseases [2].

Beyond their commercial importance, oranges are well known for their health benefits, being a rich source of vitamin C, dietary fibre, antioxidants, and essential minerals [3]. Regular consumption of oranges supports immune function, cardiovascular health, digestion, and overall well-being. Economically, oranges make a significant contribution to rural livelihoods, export revenues, and agro-industrial development in many countries. Therefore, ensuring fruit quality through advanced management strategies is essential to sustain productivity, meet global demand, and minimise post-harvest losses [4].

Despite their importance, orange fruits are highly susceptible to diseases such as citrus canker, melanose, and fungal infections that manifest as visible lesions, discoloration, and surface deformities. If not detected at an early stage, these diseases can rapidly spread during harvesting, storage, and transportation, leading to severe quality degradation [5]. Traditional disease inspection methods, which rely primarily on manual visual assessment, are often labour-intensive, subjective, and inadequate for large-scale or real-time applications. These limitations have accelerated the adoption of artificial intelligence (AI) and image-based computer-aided systems for automated fruit disease diagnosis [6].

Recent advances in machine learning (ML) and deep learning (DL), particularly convolutional neural networks (CNNs), have demonstrated remarkable performance in agricultural IMAGE ANALYSIS. Pre-trained deep networks combined with transfer learning have proven highly effective in extracting discriminative features from complex image data. Such models are capable of learning rich feature representations and adapting them to specific agricultural tasks, making them particularly suitable for fruit disease detection and classification.

However, most existing approaches primarily rely on end-to-end deep learning models without adequately addressing feature redundancy, noise sensitivity, and the need for effective integration of pre-processing and feature optimization techniques. Furthermore, limited attention has been given to hybrid frameworks that combine classical image enhancement with deep feature extraction and sparse learning to improve generalization and robustness in multi-class disease classification.

In this work, an automated orange fruit disease detection and classification framework is proposed by integrating a ResNet50-based deep feature extractor with a Stacked Sparse Auto Encoder (SSAE) classifier, referred to as the RSNT-SSAE model. Initially, Wiener filter-based noise removal is applied to suppress image noise, followed by CLAHE-based contrast enhancement to improve visual clarity. Color-based segmentation using RB thresholding is then employed to isolate disease-affected regions on the fruit surface. Deep features are extracted using the ResNet50 architecture, and final classification is performed using SSAE to achieve accurate multi-class disease recognition. The proposed model demonstrates high effectiveness, achieving an

accuracy of 98.10%, thereby enabling reliable and automated disease diagnosis.

The remainder of this paper is organized as follows: Section 2 reviews related works on fruit disease detection. Section 3 details the proposed RSNT-SSAE methodology. Section 4 presents experimental results and performance analysis. Finally, Section 5 concludes the study and outlines future directions.

2. RELATED WORKS

The study [7] is focused on how to use DenseNet-121 as a deep learning-based structure to identify diseases in orange crops (black spot and greening), while utilizing transfer learning and image enhancement techniques with a database that contains 1,164 images and achieved an average classification rate of 97.4% for identifying both healthy and diseased orange crops. This research demonstrates how deep learning can help automate disease identification in agriculture, enhance agricultural efficiency and reduce costs. In [8], Convolutional Neural Network (CNN) based classification was used with Pretrained CNN models (specifically ResNet-50), as well as employing a Context Data Fusion technique with Faster-CNN on Edge Computing platforms to classify the orange fruit images into a class of fresh or one of three possible disease classifications and achieve high performance evaluation metrics that include accuracy rates of 92.17% for CNN and 97.28% for ResNet-50.

In [9], The authors employed a faster-CNN model in an Edge Computing platform to detect and classify six different citrus fruit diseases (cankers, black spot, greening, scab, melanose, and normal/healthy citrus fruits) and utilized a Context Data Fusion model with transfer learning to maximize the efficiency of fruit disease detection by combining images from two distinct visual patterns (RGB and NIFR). Study [10] utilized the latest transfer learning-based models (ResNet50, InceptionV3, MobilenetV2 and EfficientNetB3) to better classify disease in the Citrus Plant Dataset, and found that the model EfficientNetB3 performed best in all categories, including training (99.43%), validating (99.48%) and testing (99.58%) accuracy.

Study [11] focused on the detection and classification of diseases found in oranges utilizing deep learning techniques, specifically the MobileNetV2 model. It utilized transfer learning utilizing pre trained weights from ImageNet, and data augmentation, as well as a stratified dataset for training, validation and testing. The results

demonstrated that the model had a validation accuracy of 98.66%, thus confirming its ability to diagnose orange disorders through image analysis. The study [12] investigated the application of several machine learning methods (including deep learning techniques), such as Convolutional Neural Networks (CNN), specifically those based on MobileNetV2, to detect and classify different types of diseases affecting oranges. The CNN method was used to identify four categories of orange diseases – Blackspot, Canker, Fresh and Greening. The results showed that the CNN-based models were able to analyze the images of the fruits with high levels of accuracy. Specifically, this model was able to achieve an overall accuracy level of 98.22%. This is indicative of how advanced architectures can be effective for the detection of diseases affecting agricultural products.

In another study [13], researchers utilized a deep learning-based system to classify diseases affecting oranges using the MobileNetV2 neural network architecture. The researchers had access to a total of 1090 images obtained from a public data set on Kaggle, which they divided into two subsets – a training subset and a validation subset. In addition to utilizing transfer learning to utilize previously developed, pre-trained feature extraction layers within the MobileNetV2 architecture, the researchers also included Dropout layers and Average Pooling layers to enhance the ability of the model to generalize across different inputs. The model was trained for a period of 10 epochs at a batch size of 32 and achieved a validation accuracy rate of 95.00%.

A hybrid model combining a support vector machine (SVM) for classification and a convolutional neural network (CNN) for feature extraction was proposed in this paper [14], by utilizing the benefits of each model for the classification of 6 common disorders of oranges. In the evaluation of the model, the authors utilized a dataset of 4,864 photos of oranges; the model achieved an accuracy of 88.13%. Through their sensitivity analysis, the authors found that the form, size, and texture of the lesions were the three most important features for distinguishing between different orange diseases.

Study [15], a transfer learning- based method was proposed to detect citrus diseases using Deep Convolutional Neural Network (CNN) architectures, namely, InceptionV3, ResNet50, VGG16 and VGG19, along with data augmentation to increase the performance of classification and the use of several evaluation metrics to compare the

performance. The experimental results indicated that VGG19 has the highest accuracy of 99.89%, thus demonstrating the applicability of Transfer Learning in reducing the computational costs. All the steps are explained in detail in the subsequent sections.

3. PROPOSED WORK

The proposed RSNT-SSAE methodology follows a structured and efficient workflow, as illustrated in Fig. 1. The process begins with a Wiener filter – based noise removal, which effectively suppresses noise present in orange fruit images while preserving essential surface details and texture patterns associated with fruit diseases and prepares for subsequent processing. Following noise removal, Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to enhance local contrast and improve the visibility of disease symptoms such as discoloration, lesions, and surface irregularities. Next, color-based segmentation using RGB thresholding is employed to accurately separate disease-affected regions from healthy portions of the orange fruit. After segmentation, deep feature extraction is performed using the ResNet50 model, which leverages transfer learning to capture high-level and discriminative features related to different disease patterns. The extracted deep features are then fed into a Stacked Sparse Auto Encoder (SSAE) classifier, which effectively learns hierarchical feature representations and performs accurate multi-class classification of orange fruit diseases. The SSAE enhances classification performance by reducing redundancy and emphasizing the most informative features. Detailed descriptions of each processing stage, including pre-processing, segmentation, feature extraction, and classification, are presented in the subsequent sections.

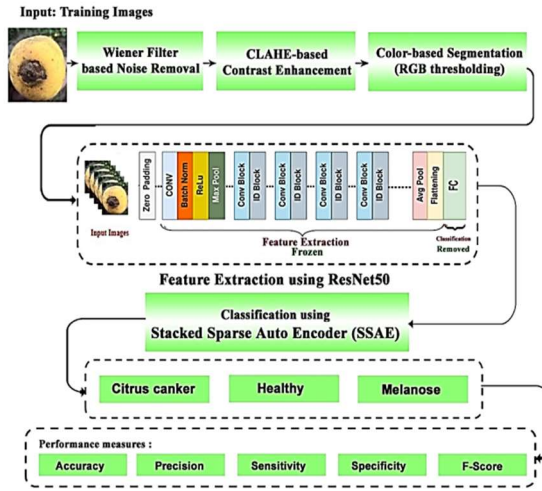


Fig. 1. Overall workflow of the proposed RSNT-SSAE model

3.1 Wiener Filter – based noise removal

The Wiener filter is a widely adopted technique for image restoration and noise reduction, particularly effective in applications where images are degraded by additive noise and blur. In the context of orange fruit disease detection and classification, Wiener filtering plays a crucial role in enhancing image quality while preserving important surface details. Orange fruit images captured in natural or semi – controlled environments often suffer from noise introduced by lighting variations, sensor limitations, and environmental conditions. The Wiener filter addresses these challenges by minimizing the mean square error between the original and the restored image, thereby improving clarity before disease analysis, as illustrated in Fig. 2.

The Wiener filter is mathematically expressed as shown in Eq. (1):

$$\hat{I}(u, v) = \frac{H^*(u, v)}{|H(u, v)|^2 + \frac{S_n(u, v)}{S_i(u, v)}} G(u, v) \quad (1)$$

In Eq. (1), where:

- $\hat{I}(u, v)$ represents the restored image in the frequency domain.
- $G(u, v)$ denotes the degraded input image.
- $H(u, v)$ is the degradation function, and $H^*(u, v)$ is its complex conjugate.
- $S_n(u, v)$ and $S_i(u, v)$ represent the power spectral densities of the noise and the original image, respectively.

The Wiener filter operates by estimating the local image statistics and adaptively adjusting the

filtering process to reduce noise while preserving important structural and textural information [16]. When applied to orange fruit images, this adaptive behavior ensures that disease – related features such as lesions, spots, discolorations, and surface irregularities are retained, which are critical for accurate segmentation and feature extraction. By effectively suppressing noise without over-smoothing the fruit surface, Wiener filtering enhances the performance of subsequent processing stages, including contrast enhancement, segmentation, and deep feature extraction. As a result, it contributes significantly to improving the reliability and accuracy of the proposed automated orange fruit disease detection framework.

3.2 CLAHE – based Contrast Enhancement

In the proposed orange fruit disease detection framework, contrast enhancement is an essential pre – processing step to improve the visibility of disease -affected regions. Orange fruit images often suffer from uneven illumination and surface reflections, which can obscure subtle signs of disease. To address this issue, Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied before segmentation. CLAHE enhances local contrast by dividing the image into small, non-overlapping tiles and performing histogram equalization on each tile independently [17]. This localized approach is particularly effective for highlighting low-contrast disease spots and surface irregularities. To prevent noise amplification, a clip limit is used, and bilinear interpolation is applied to smoothly merge neighboring tiles.

In this study, CLAHE is applied to the luminance (L) channel after converting the image to the LAB color space, ensuring that brightness is enhanced while preserving essential color information. As shown in Fig. 2, CLAHE significantly improves the visibility of lesions and texture details, facilitating accurate segmentation and feature extraction. This step enhances the system's robustness against varying lighting conditions and improves its overall performance.

3.3 Color – based Segmentation (RGB thresholding)

Thresholding based on the color of an image, using RGB (red, green and blue), is useful for separating areas of an orange fruit that may have a disease. Thresholding is especially helpful when trying to find areas where a disease has caused color to change on an orange fruit, such as dark brown spots, white patches or yellowing. Since color is a primary factor used to determine if a

disease exists, using thresholding to separate the colors associated with a disease will help identify the area of the orange fruit affected by the disease. When an image is processed through an appropriate range of thresholds for each of the three RGB color channels, the resulting separated image shows the areas of the image that could possibly show signs of a disease [18]. In addition, since this method separates the area of the fruit most likely to have a disease, the method significantly minimizes unnecessary data processing, while also minimizing the amount of time needed to process the images. Segmented regions provide significant amounts of valuable data to use in determining the type of disease that exists, including color distribution, texture, and the general shape of the region, as depicted in Fig. 2.

Using RGB thresholding improves the accuracy of identifying diseases of oranges because it brings out the differences in color between areas of a disease on the fruit and the rest of the fruit. Also, RGB thresholding is easy to implement and requires minimal computer resources to perform the necessary computations, making it useful for use in real-time or near-real-time applications. RGB thresholding allows for adjustments to be made to the threshold values based upon the specific color characteristics of the diseases of the orange fruit and/or lighting conditions under which the images were taken, allowing the thresholding method to be applied to a variety of different datasets. RGB thresholding is also used as a pre-processing step to remove unwanted/irrelevant data (noise) before extracting features and classifying the images.

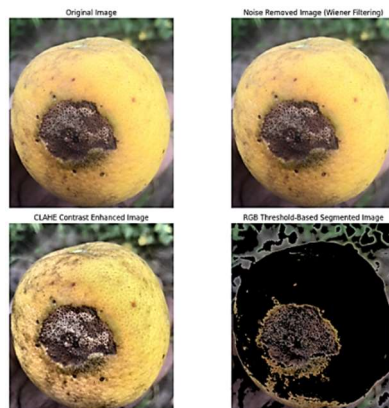


Fig. 2. Visual results of pre-processing and RGB threshold-based segmentation on orange fruit images

3.4 Feature Extraction using ResNet50

In the proposed framework for detecting the diseases affecting oranges, the feature extraction phase is critical because it takes the segmented

images and creates higher-level representations that will be appropriate for the classification process. For the feature extraction process in this study, the ResNet50 deep convolutional neural network has been utilized due to extensive literature demonstrating the ResNet50 network's ability to extract complex yet highly discriminatory features from images.

The ResNet50 is a 50-layer deep residual network that utilizes skip (residual) connections to mitigate the vanishing gradient problem and facilitate the efficient training of deep architectures. The use of residual connections allows the network to learn complex visual patterns while at the same time preserving the stability of the gradient flow, which makes it highly suitable for various forms of agricultural image analysis tasks. Transfer learning is a key aspect of utilizing the pre-trained ResNet50 model trained on the ImageNet dataset. The fully connected (top) layers of the pre-trained ResNet50 model were frozen during the training process so that the generic features, including the edges, textures and shape patterns that were learned by the model during training [19] would remain intact as depicted in Fig. 3. The freezing of the top layers of the network resulted in reduced computational complexity, prevented the phenomenon of overfitting and facilitated an effective extraction of features from the limited number of available images of the segmented orange fruits. The segmented orange fruit images were then passed through the convolutional layers of the ResNet50 model, and the output of the final convolutional block was extracted as deep feature vectors. The features captured by the deep feature vectors include the essential visual characteristics of the disease symptoms, such as discolorations, lesions, and variations in texture on the surface of the fruit.

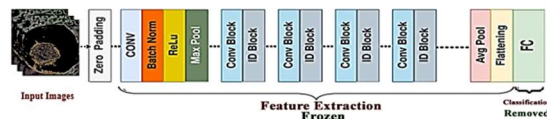


Fig. 3. Feature Extraction using ResNet50

The deep features extracted from the images serve as the robust input to the subsequent classification stage, thereby resulting in the enhancement of the overall accuracy and reliability of the disease detection system. By freezing the top layers of the model, the proposed method provides a good balance between the computational efficiency of the model and the high discriminative power of the model, which contributes greatly to

achieving the classification accuracy of 98.10% of the model.

3.5 Classification Using SSAE

Orange fruit disease classification is performed here in a Stacked Sparse Auto Encoder (SSAE) architecture, a model that is a deep learning-based method for performing unsupervised feature extraction and is also very effective at classification. Since the SSAE model is so good at extracting hierarchically discriminative representations while reducing the number of redundant features in large-dimensional data spaces created by CNNs like ResNet50, the SSAE model has been chosen as the best choice for this study. The SSAE architecture is composed of multiple sequential sparse autoencoder layers [20]. Each of these auto encoders learns an abstraction of the input feature set by minimizing the reconstruction error while constraining the sparsity of the weights using an L1 penalty during training. Using a sparsity constraint, the network will only select the most informative features, resulting in better class separability and classification results. The deep features learned from the frozen ResNet50 model are used as the input to the SSAE model. In a greedy, layer-by-layer fashion, each autoencoder layer is trained to find meaningful abstractions in the feature space. Once all of the layers have been trained using an unsupervised approach, a new classification layer is added on top of the stacked auto encoders to classify the image inputs as being one of two classes: healthy or diseased.

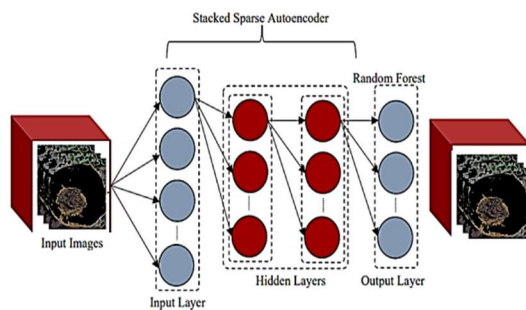


Fig. 4. Architecture of SSAE used for orange fruit disease classification

Fig. 4 illustrates the SSAE classification model. Deep feature vectors from pre-processed and segmented images of orange fruits are fed into the input layer of the SSAE classification model. As the feature vectors progress through the layers of the SSAE, increasingly abstracted and compact representations of the input features are learned. Each of the hidden layers of the SSAE model

captures different disease-related characteristics such as surface color changes, textures of lesions, and shape irregularities. The final representation of the input features is then passed to the output layer for disease classification.

Table 1. Hyperparameter values used for the proposed RSNT-SSAE framework

Parameter	Value / Description
Input Feature Dimension	ResNet50 deep feature vector
Number of Autoencoder Layers	3 (Stacked)
Hidden Neurons (Layer 1)	1024
Hidden Neurons (Layer 2)	512
Hidden Neurons (Layer 3)	256
Sparsity Regularization	L1 regularization
Sparsity Penalty Coefficient	0.001
Activation Function	ReLU
Optimization Algorithm	Adam
Learning Rate	0.001
Batch Size	32
Number of Training Epochs	50
Output Layer Neurons	3 (Citrus canker, Healthy, Melanose)
Loss Function	Categorical Cross-Entropy

The detailed hyperparameter configuration of the SSAE classifier used for orange fruit disease classification is summarized in Table 1. The SSAE classification model is capable of modeling the non-linear relationships present in the deep feature space of the input features and improving the classification accuracy and the reliability of the classification model. The use of ResNet50 for extracting features from images and the SSAE for classification provides a precise and reliable means for detecting diseases in oranges. The classification accuracy was determined to be 98.10%.

3.6 Comparison with prior work

To distinguish between the proposed RSNT-SSAE framework, and previous research (state of the art) a comparative study will be conducted on the current RSNT-SSAE framework to several other state of the art frameworks which include

AlexNet [22], VGG-16 [22], GoogleNet [22], ResNet [22], DenseNet [22], and VGG16-CNN [23] as outlined in Table 3; unlike some previous methodologies that are primarily based upon image classification, the RSNT-SSAE methodology utilizes an integration of deep feature extraction via a pre-trained ResNet50 for the extraction of features, and then employs a Stacked Sparse Autoencoder (SSAE) for the extraction of sparse features. The majority of previously established methodologies have not taken into consideration the reduction of redundant features or the issue of generalization within the context of multi-class disease detection. In contrast to existing approaches, the proposed framework uniquely combines noise reduction, contrast enhancement, and region-based segmentation before deep feature extraction, ensuring higher quality input features. Furthermore, the use of SSAE instead of conventional SoftMax classifiers enables effective feature compression and improved class separability, which is not commonly addressed in earlier studies. These differences significantly contribute to the improved robustness and classification accuracy achieved by the proposed model. Through the combination of transfer learning and sparse feature learning, the RSNT-SSAE methodology has achieved both enhanced classification accuracy and greater robustness than previously established methodologies for detecting orange fruit diseases.

3.7 Novelty and Contributions

Although the individual components employed in this study – Wiener filtering, CLAHE, RGB thresholding, ResNet50, and Stacked Sparse Autoencoders – are well established, the novelty of this work lies in the systematic integration and optimization of these techniques into a unified hybrid framework for orange fruit disease detection and classification. Unlike conventional end-to-end deep learning approaches, the proposed RSNT-SSAE model combines classical image enhancement, color-based segmentation, deep feature extraction, and sparse feature learning in a sequential and complementary manner. In particular, the proposed approach differs from existing studies by explicitly addressing feature redundancy and noise sensitivity through a hybrid pipeline, rather than relying solely on deep neural networks. This integrated design enables improved generalization and robustness, especially in multi-class classification scenarios, thereby providing a more reliable solution compared to conventional

standalone deep learning models reported in the literature.

The main contributions of this study are summarized as follows:

- An optimized hybrid pipeline that integrates classical image processing and deep learning for enhanced feature quality and robustness in orange fruit disease classification.
- A sparse feature learning strategy using SSAE after deep feature extraction, reducing redundancy and improving classification generalisation compared to conventional Softmax-based classifiers.
- A comprehensive ablation analysis demonstrating the individual and collective contributions of each processing stage, validating the effectiveness of the proposed integration strategy.
- Extensive experimental validation showing superior performance over several state-of-the-art CNN architectures on a public orange fruit dataset.

4. EXPERIMENTAL RESULTS

4.1 Implementation Setup

Experimental validations were used to test the efficiency of the developed RSNT-SSAE-based classification model for the recognition and categorization of orange fruit diseases. The experimental validations were executed on healthy and diseased orange fruit images. All experiments were run by utilizing the Python 3.6.5 programming language on the same computer hardware as that described above (Intel i5-8600K processor; 16 GB RAM; 250 GB SSD; 1 TB HDD; NVIDIA GeForce GTX 1050 Ti GPU with 4 GB memory). The accuracy of the proposed classification model was evaluated through the use of common metrics for evaluating classification models, including accuracy, sensitivity, specificity, precision and F-Score, to assess the classification model's performance comprehensively.

The Orange_Fruit dataset was used for conducting the experimental validation, and this dataset was obtained from the Kaggle repository [21]. The original dataset included 3000 images of oranges infected with citrus canker, 3000 images of healthy oranges and 2600 images of oranges infected with melanose. The original dataset exhibited an unbalanced class distribution, specifically due to the reduced number of

melanose-infected image examples. Therefore, a data balancing technique was employed to allow for the creation of an unbiased and fair learning platform. To create this balanced dataset, images representing citrus canker and healthy oranges were selected in the ratio of 2600/2600 to provide 2600 images per disease class. The use of the balanced dataset configuration will contribute to the development of a robust classification model and prevent biased classification results based on the majority disease class during training and evaluation. Images representative of the disease classes, along with characteristics associated with each image, are presented in Fig. 5. Additionally, the complete dataset distributions are provided in Table 2.

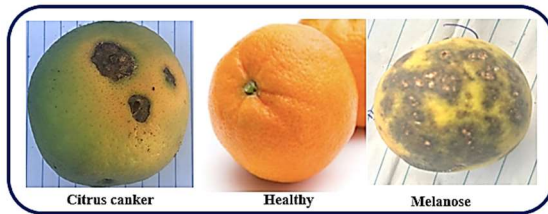


Fig. 5. Sample Images

Table 2. Dataset Description

Class	No. of. Samples
Citrus canker	2600
Healthy	2600
Melanose	2600
Total	7800

4.2 Discussions and Observations

The Confusion Matrix in Fig. 6 displays how the proposed RSNT-SSAE model performed in classifying the Orange Fruit Diseases, i.e., Citrus Canker, Healthy and Melanose, and also shows the misclassification patterns. Table 3 provides a summary of the quantitative analysis of the RSNT-SSAE framework and illustrates its ability to diagnose diseases on oranges in the test and train phases. To assess the reliability of the model's performance, the data set was divided 70% for the training phase and 30% for the test phase. Results from the RSNT-SSAE model were highly accurate and capable of identifying classes (disease or no disease) with an overall accuracy of 98.10%. Additionally, it provided a precision of 97.87%, a sensitivity of 97.83%, an F-score of 97.85% and a specificity of 98.37% during the testing phase. All of these statistics illustrate that the RSNT-SSAE model has a high level of discrimination and is able

to distinguish healthy oranges from those with diseases.

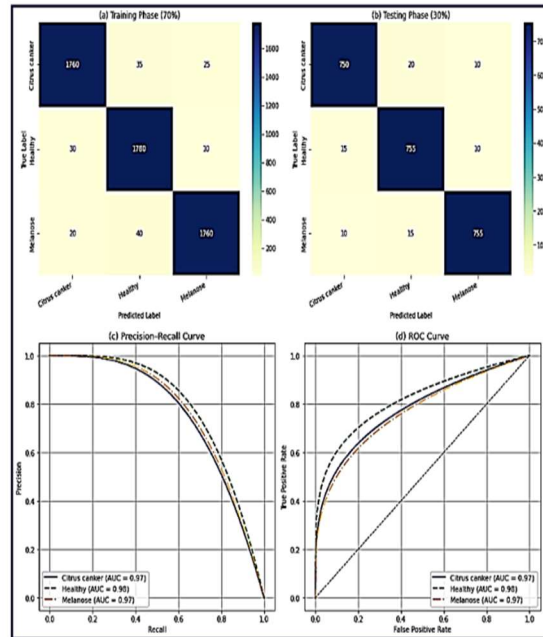


Fig. 6. (a) Confusion matrix based on the TR set, (b) Confusion matrix based on the TS set, (c) Precision – Recall Curve, (d) ROC Curve

Performance of the proposed RSNT-SSAE model in Fig. 7 has been assessed based on several parameters, such as Accuracy, Precision, Sensitivity, Specificity and F-score for each class of orange fruit disease that are included in the dataset to be trained. The RSNT-SSAE model achieved an accuracy of 97.90%, precision of 97.60%, specificity of 98.10%, sensitivity of 97.40%, and an F-score of 97.50% for Citrus Canker Class; it was also able to achieve superior performance (accuracy of 98.40%, precision of 98.20%, specificity of 98.60%, sensitivity of 98.10%, and an F-score of 98.15%) for the Healthy Class; finally, the RSNT-SSAE model achieved an accuracy of 97.80%, precision of 97.50%, specificity of 98.00%, sensitivity of 97.30%, and an F-score of 97.40% for Melanose Class. In addition to being effective in discriminating among all classes of orange fruit diseases in the training dataset, these results show the high level of consistency and effectiveness of the proposed model.

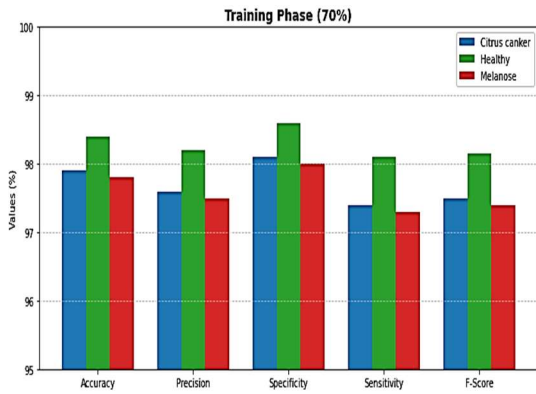


Fig. 7. Outcomes of the proposed RSNT-SSAE model on 70% of the training dataset

Fig. 8 shows the evaluation of the classification performance of the proposed RSNT-SSAE model using Accuracy, Precision, Sensitivity, Specificity, and F-score metrics during the testing phase. The RSNT-SSAE model achieved an accuracy of 98.10%, a precision of 97.90%, a specificity of 98.40%, a sensitivity of 97.80%, and an F-score of 97.85% for Citrus Canker Class. In addition to this, the RSNT-SSAE model demonstrated a remarkable performance in terms of its ability to classify healthy oranges by achieving an accuracy of 98.70%, a precision of 98.50%, a specificity of 98.90%, a sensitivity of 98.60%, and an F-score of 98.55%. Finally, the RSNT-SSAE model recorded an accuracy of 97.50%, a precision of 97.20%, a specificity of 97.80%, a sensitivity of 97.10%, and an F-score of 97.15% for Melanose Class. In addition to demonstrating a good capacity to generalize and robustness, the RSNT-SSAE model was also capable of effectively classifying orange fruits under new data conditions.

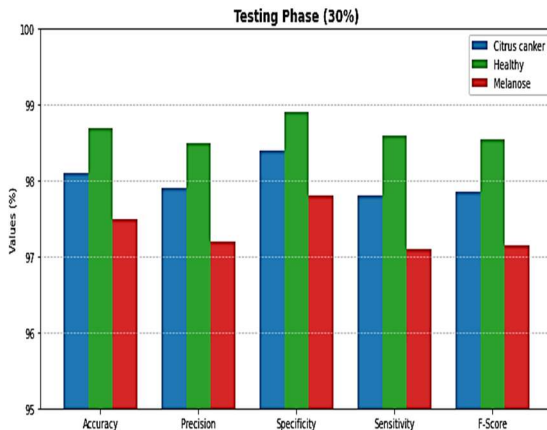


Fig. 8. Outcomes of the proposed RSNT-SSAE model on 30% of the testing dataset

Table 3. Outcomes of the RSNT-SSAE model for orange fruit disease detection and classification

Training Phase (70%)					
Class	Accuracy (%)	Precision (%)	Specificity (%)	Sensitivity (%)	F-Score (%)
Citrus canker	97.90	97.60	98.10	97.40	97.50
Healthy	98.40	98.20	98.60	98.10	98.15
Melanose	97.80	97.50	98.00	97.30	97.40
Average	98.03	97.77	98.23	97.60	97.68
Testing Phase (30%)					
Class	Accuracy (%)	Precision (%)	Specificity (%)	Sensitivity (%)	F-Score (%)
Citrus canker	98.10	97.90	98.40	97.80	97.85
Healthy	98.70	98.50	98.90	98.60	98.55
Melanose	97.50	97.20	97.80	97.10	97.15
Average	98.10	97.87	98.37	97.83	97.85

As seen in Table 4, all other existing architectures, AlexNet [22], VGG-16 [22], GoogleNet [22], ResNet [22], DenseNet [22], VGG16-CNN [23], have lower accuracy rates than the RSNT-SSAE model. Their accuracy was approximately 88.18%, 90.47%, 91.73%, 91.85%, 92.46%, and 93.66%, respectively; while the RSNT-SSAE model has a high accuracy of 98.10%. In addition, their sensitivity values are all much lower than those of the RSNT-SSAE model, at 87.40%, 89.00%, 90.20%, 90.60%, 92.30%, and 93.10%, respectively; and therefore, they are less effective in detecting diseased orange fruit samples. The RSNT-SSAE model has a high sensitivity of 97.83%, which is evidence of its ability to minimize false negatives. Precision also revealed that the existing models' precision values were between 87.90% and 93.40%, and the RSNT-SSAE model has a high precision of 97.87%, which is evidence of better reliability in predicting diseases. Furthermore, the F-score metric, which evaluates both the precision and sensitivity, indicated that the existing models had lower values of F-scores than the RSNT-SSAE model. While the existing models ranged from 87.65% to 93.25%, the RSNT-SSAE model achieved an F-score of 97.85%, showing good overall classification performance. These results show that the proposed RSNT-SSAE framework improves both accuracy and reliability compared to existing models by effectively addressing noise sensitivity and feature redundancy. Unlike conventional approaches, it enhances generalization through the integration of transfer learning and sparse feature optimization, resulting in a more robust model. This

demonstrated that the integration of ResNet50 for extracting deep features with the Stacked Sparse Autoencoder classifier improves the disease classification accuracy significantly. Fig. 11 shows the graphical comparison of the RSNT-SSAE model and the existing models and illustrates its superiority.

As shown in Fig. 9, the proposed RSNT-SSAE model's Training Accuracy (TACY) and Validation Accuracy (VACY) show an upward trend as the number of training epochs increases; this demonstrates that the proposed model is able to effectively learn the data and converge to a consistent solution. In addition, the TACY and VACY values remain relatively stable during each epoch; in fact, the VACY generally has a high value compared to TACY for most of the epochs, which indicates that the proposed model can generalize well and has minimal overfitting. Therefore, it can be concluded that the proposed RSNT-SSAE model was able to achieve its best TACY and VACY values at the final epoch and thus was able to extract discriminative features from the data efficiently. Overall, the results indicate that the RSNT-SSAE model is reliable and provides excellent performance when classifying oranges with disease.

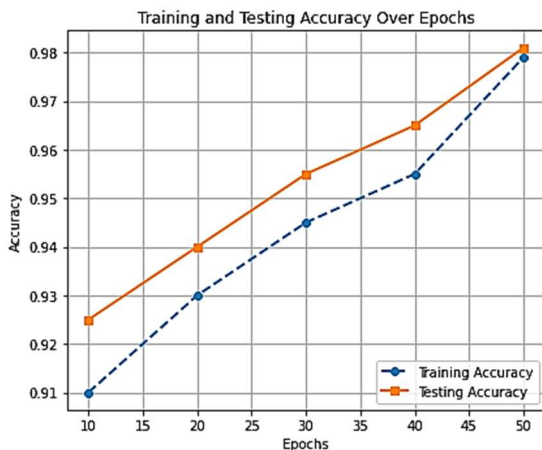


Fig. 9. Accuracy graph based on the training and testing data

Fig. 10 illustrates the Training Loss (TLOS) and Validation Loss (VLOS) of the proposed RSNT-SSAE Model during each training epoch, indicating that both Training and Validation Loss decrease consistently with increasing epochs, signifying effective learning and successful convergence of the proposed model. A strong correlation between TLOS and VLOS demonstrates stability during training and an absence of overfitting. It is evident from Figure 10 that the

minimum loss values occur after all epochs were completed, demonstrating optimal model parameterization. Overall, the trend of decreasing loss values indicates the RSNT-SSAE models' effectiveness and reliability for classifying diseases in orange fruits.

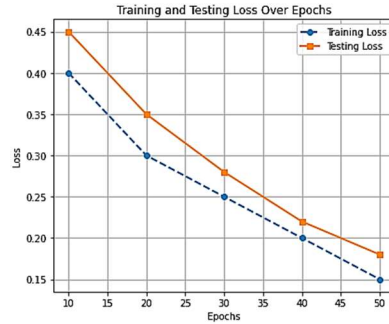


Fig. 10. Loss graph based on the training and testing data

Table 4. Assessment of the proposed RSNT-SSAE model in comparison to existing models

Model	Accuracy (%)	Sensitivity (%)	Precision (%)	F-Score (%)
AlexNet [22]	88.18	87.40	87.90	87.65
VGG-16[22]	90.47	89.80	90.10	89.95
GoogleNet [22]	91.73	91.10	91.40	91.25
ResNet [22]	91.85	91.30	91.60	91.45
DenseNet [22]	92.46	91.90	92.20	92.05
VGG16-CNN [23]	93.66	93.10	93.40	93.25
Proposed RSNT-SSAE	98.10	97.83	97.87	97.85

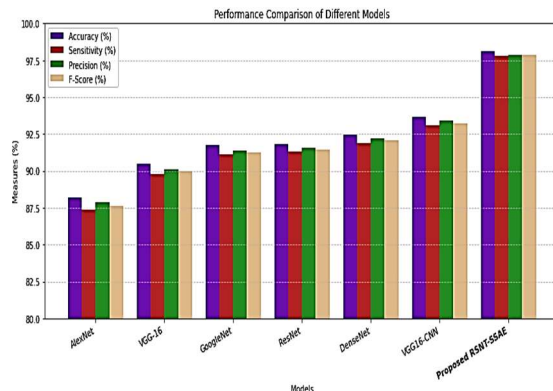


Fig. 11. Overall Analysis of the existing models with the proposed RSNT-SSAE model

4.3 Discussion of Ablation Results

The ablation results clearly indicate that each component of the proposed framework contributes positively to the overall classification performance

depicted in Table 5. The baseline ResNet50 model with a Softmax classifier achieves an accuracy of 91.85%, demonstrating the effectiveness of deep feature extraction alone. Incorporating Wiener filtering improves noise suppression and results in a noticeable performance gain. The addition of CLAHE further enhances local contrast, improving local contrast, improving the visibility of disease-related features. Introducing RGB threshold disease-affected regions and reducing background interference. Furthermore, replacing the Softmax classifier with an SSAE leads to improved performance by enforcing sparsity and reducing redundancy in the deep feature space.

Table 5. Ablation study of the proposed RSNT-SSAE framework

Configuration	Wiener Filter	CLAHE	RGB Segmentation	Classifier	Accuracy (%)
ResNet50 + Softmax	X	X	X	Softmax	91.85
+ Wiener Filter	✓	X	X	Softmax	93.20
+ Wiener + CLAHE	✓	✓	X	Softmax	94.60
+ Wiener + CLAHE + RGB Segmentation	✓	✓	✓	Softmax	96.10
ResNet50 + SSAE (no segmentation)	X	X	X	SSAE	95.40
Proposed RSNT-SSAE (Full Pipeline)	✓	✓	✓	SSAE	98.10

The highest accuracy of 98.10% is achieved when all components are integrated into the complete RSNT-SSAE framework. This confirms that the proposed method is not merely a combination of existing techniques but an optimized hybrid pipeline in which each stage enhances the effectiveness of subsequent processing steps.

4.4 Critique and Limitations

The high accuracy of the proposed RSNT-SSAE model is notable for detecting the disease of orange fruits, the potential of the model can be limited by several factors. For example, an extreme variation in lighting conditions or a variety of complex background environments, etc., can affect the performance of the model. Also, it is assumed that the model will have good performance for all types of orange fruits due to their differences in visual appearance; this assumption may be

incorrect since each type of orange has different visual characteristics from others. However, the current method uses RGB image data; therefore, there is a possibility that the subtle disease symptom is not captured through the use of RGB images and is not visible to the system. Therefore, in future research, possible ways to improve the accuracy of the model would include using data augmentation techniques extensively, using multi-seasonal and geographic data sets, and possibly adding other imaging modalities such as hyperspectral or thermal imaging data. Additionally, it is assumed that all of the data in the training data set is fully labelled; therefore, possible ways to extend the method to semi-supervised or self-supervised methods could increase the ability to scale up the system while reducing the amount of labelling required for large-scale agricultural applications.

4.5 Practical Implications

The proposed RSNT-SSAE framework offers significant practical value for real-world agricultural applications, particularly in the context of precision farming and smart agriculture. By enabling automated and accurate detection of orange fruit disease, the system can assist farmers in early diagnosis, thereby reducing crop losses and improving overall yield quality. The integration of image processing and deep learning techniques makes the model suitable for deployment in mobile-based applications, edge devices, and IoT-enabled agricultural monitoring systems. Furthermore, the framework can be incorporated into drone-based imaging systems for large-scale orchard surveillance, allowing continuous and real-time disease monitoring. In the current industry scenario, where there is an increasing demand for sustainable and technology-driven farming practices, the proposed model provides a cost-effective and scalable solution for enhancing productivity and decision-making in citrus cultivation.

5. CONCLUSION

This study provides a successful RSNT-SSAE-based hybrid model for the automatic identification and categorization of diseases on oranges. This research comprises three primary components: image pre-processing to remove noise from images, color-based segmentation of orange images using RGB thresholding, deep feature extraction of images via ResNet50, and robust classification via Stacked Sparse Autoencoder (SSAE). The primary objective of this research was to develop a reliable

and efficient model capable of overcoming the limitations of traditional inspection methods and existing deep learning approaches in terms of feature redundancy, noise sensitivity, and classification accuracy. The experiments demonstrated that the RSNT-SSAE model can accurately detect diseases with an accuracy of 98.10% and outperformed existing deep-learning models such as AlexNet, VGG-16, GoogleNet, ResNet, and DenseNet on several measures, confirmed the superiority of the proposed approach in effectively distinguishing between healthy and infected orange fruit images. The most important contribution to this research was combining the power of transfer learning (i.e., utilizing pre-trained deep representations) with sparse feature learning to increase classification accuracy, decrease redundant features, and enhance the ability of the model to generalize. Furthermore, the findings indicate that the integration of classical image enhancement techniques with deep learning contributes significantly to improving feature quality and model generalization. Results from this research validated the effectiveness of the proposed RSNT-SSAE model as an effective decision-making support tool for early orange disease detection, allowing farmers to intervene on time to reduce crop loss and promote sustainable agriculture.

5.1 Open challenges and future directions

The RSNT-SSAE has demonstrated potential for use in orchards. However, there are still many challenges that need to be addressed before it can be used in an operational environment. The main challenges include increasing real-time processing performance on resource-constrained edge computing devices, developing greater resistance to a variety of environmental conditions (e.g., lighting, temperature), and decreasing reliance upon expensive manual labelling of training images. The next step could include integrating the system with AI-edge platforms, IoT sensor systems and/or drone-based imaging systems to allow for constant monitoring of the orchard and precision agriculture. The collaborative involvement of agricultural professionals and plant pathologists will be required to verify the accuracy of the model for multiple growing regions, as well as to increase the scope of the framework to cover a wider array of citrus-related diseases.

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