ENHANCED DISEASE DETECTION THROUGH IMAGE FUSION IN *Solanum Tuberosum* L.

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ABSTRACT

Disease detection in agricultural crops, such as Solanum tuberosum L. (potato), is of utmost importance to ensure crop health and maximize yield. Traditional methods for disease detection in potatoes rely on manual inspection, which can be time-consuming and prone to human error. Image processing and machine learning techniques have shown promise in automating disease detection processes. This study proposes a novel approach for disease detection in Solanum tuberosum L. by leveraging image fusion techniques. The proposed method involves the fusion of multiple images of potato plants, acquired using different sensors or imaging modalities, to create a comprehensive and informative representation of the crop. Image fusion methods, such as discrete wavelet transform and continuous wavelet transform, are employed to combine the spectral and spatial information from the images effectively. The different image fusion rule is applied to the input images and resultant fused images, where relevant features are extracted to distinguish between healthy and diseased potato plants. The training dataset comprises diverse samples of both healthy and diseased potato plants, captured under various environmental conditions and disease stages. The performance of the proposed disease detection system is evaluated using standard metrics such as entropy. The results demonstrate the effectiveness of the image fusion approach in accurately identifying diseased potato plants, achieving high detection accuracy and generalization capabilities. The potential benefits of this paper include providing farmers and agricultural experts with an efficient and reliable tool for early disease detection in potato crops. Early detection can lead to timely intervention, minimizing crop losses and optimizing agricultural practices. The proposed methodology also lays the groundwork for future research in using advanced image processing techniques and machine learning algorithms for disease detection in other agricultural crops, contributing to the overall improvement of crop management and food security.

Keywords: Potato Image, Pre-Processing, Image Fusion, Discrete Wavelet Transform (DWT), Fusion Rule, Continuous Wavelet Transform (CWT).

INTRODUCTION

Potato (*Solanum tuberosum* L.) is one of the most important staple crops globally, serving as a critical food source and a key agricultural commodity (Bruckner et al., 2019). However, the cultivation of potatoes is frequently threatened by a range of diseases, which can significantly impact yield and quality (Stark et al., 2020). Timely and accurate detection of these diseases is crucial for effective management and mitigation strategies, but traditional methods fall short due to their reliance on manual inspection and their limited ability to detect early-stage infections.

This paper has objectives related to SDGs

Technological advancements have introduced new approaches to agricultural diagnostics, with image processing and analysis emerging as powerful tools for disease detection. Among these is image fusion, a technique that combines multiple images captured through different modalities. By integrating various imaging techniques, such as visible light, infrared, and thermal imagery, image fusion can enhance the visibility of disease symptoms that might not be apparent through a single imaging method.

Image fusion techniques, such as Discrete Wavelet Transform (DWT) and Continuous Wavelet Transform (CWT), offer significant advantages in potato disease detection compared to traditional methods (Shahid et al., 2024). DWT provides a way to decompose images into different frequency components, enabling the separation and enhancement of features that are crucial for detecting disease symptoms. CWT, on the other hand, allows for multi-scale analysis, offering a more detailed and nuanced view of texture and patterns that might indicate disease (Shahid et al., 2024).

This paper focuses on leveraging image fusion techniques for the early and accurate detection of diseases in *Solanum tuberosum* L. By combining different types of images, this paper aims to improve the identification of disease symptoms, thereby facilitating more effective intervention strategies. This approach not only enhances the diagnostic capabilities but also supports the development of more precise and automated monitoring systems. This paper explores the methodology behind image fusion, its application to disease detection in potatoes, and the potential benefits of this approach in modern agriculture. This study contributes to the advancement of disease management practices and ultimately improves the health and productivity of potato crops (Degefu, 2021).

1. Related Works

The field of disease detection in *Solanum tuberosum* L. involves various approaches, including traditional methods and more advanced techniques based on image processing, computer vision, and machine learning (Charkowski et al., 2020; Meno et al., 2021; Peters et al., 2004; Shukla & Ratan, 2019).

1.1 Image Processing Techniques

Studies focused on using image processing techniques such as color segmentation, texture analysis, and shape recognition to identify disease symptoms in potato plants. These methods provided valuable insights into feature extraction from potato images but were limited in their ability to handle complex variations in lighting conditions and disease stages.

1.2 Machine Learning-Based Approaches

With the advancement of machine learning algorithms, researchers began adopting supervised and unsupervised learning techniques for potato disease detection. Classification methods like Support Vector Machines (SVM), Random Forest, and k-Nearest Neighbors (k-NN) have been explored.

1.3 Deep Learning

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have gained significant attention in the field of plant disease detection. CNNs have shown impressive results in image classification tasks, including the identification of diseases in potato plants (Gao et al., 2023).

1.4 Multi-Spectral and Hyperspectral Imaging

Studies have explored the use of multispectral and hyperspectral imaging for disease detection in potatoes (Abuley & Hansen, 2021; Adolf et al., 2020; Landschoot et al., 2017). These advanced imaging techniques provide a more detailed analysis of plants, aiding in the early identification of diseases and differentiation between various diseases (Shahid et al., 2024).

1.5 Image Fusion Techniques

Image fusion techniques, such as those based on wavelet transforms, have been employed to combine data from different sensors and imaging modalities. The fusion process aims to improve overall disease detection accuracy by integrating complementary information from various sources (Gao et al., 2023).

Wavelet Transform: This technique decomposes images into sub-images with different frequencies and then fuses the information (Zhang et al., 2017).

Principal Component Analysis (PCA): This technique is used in existing works for image fusion and can also be applied to image quality assessment (Zhang et al., 2017).

Hotelling Transform: This technique is utilized for image registration, which is a crucial step in image fusion.

Radon Transform: This technique can be used for image fusion in Radon space.

2. Material and Methods

Dataset: A diverse dataset of *Solanum tuberosum* L. (potato) plant images, including both healthy and diseased samples, was collected. The images in the dataset, as shown in Figure 1, were captured under various environmental conditions and disease stages to ensure the model's robustness.

Image Acquisition and Pre-Processing: The appropriate imaging equipment was used to capture potato plant images in RGB color. The images were pre-processed to standardize their sizes, adjust brightness and contrast, and remove any noise or artifacts.

Image Fusion: Image fusion techniques were applied to combine multiple images of the same potato plant, acquired using different sensors or modalities. Different fusion methods, such as discrete wavelet transform and continuous wavelet transform, were explored to create a comprehensive and informative representation of the potato plants.

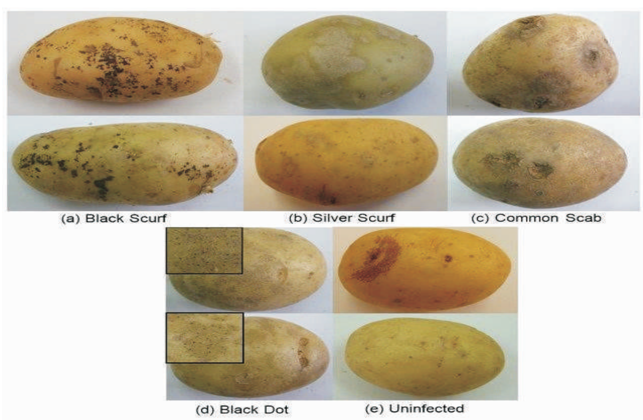

Figure 1. Potato with Different Types of Diseases

3. Methodology: Image Fusion for Potato Disease Detection

The proposed methodology for potato disease detection, shown in Figure 2, involves an image fusion technique that combines information from two different images.

3.1 Image Acquisition (Image A and Image B)

Two images of the same potato sample, captured under different conditions or from different perspectives, are taken as input for the fusion process. These images are denoted as Image A and Image B.

3.2 Discrete Wavelet Transform (DWT)

DWT is applied separately to both images (Image A and Image B). DWT decomposes each image into four sub-bands: Low-Low (LL), Low-High (LH), High-Low (HL), and High-High (HH). These sub-bands represent different frequency components of the image, capturing both approximate and detailed information.

The LL sub-band contains the approximation coefficients representing the coarse structure of the image, while the LH, HL, and HH sub-bands contain the detail coefficients representing edges and texture information at different orientations and resolutions.

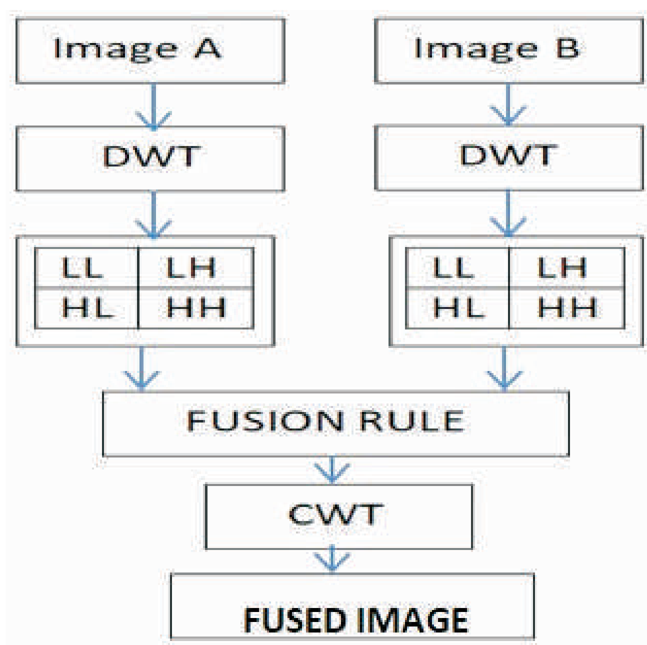

Figure 2. Work Flow Diagram

3.3 Fusion Rule

After pre-processing both images into DWT sub-bands, a fusion rule is applied. This rule is designed to select and combine the most relevant information from the sub-bands of both images.

Typically, the fusion rule selects the coefficients from either Image A or Image B based on specific criteria, such as maximum absolute values, entropy, or spatial frequency. The aim is to retain the most informative features from both images, leading to a fused set of sub-bands that contains a rich representation of the original images.

3.4 Continuous Wavelet Transform (CWT)

Once the fusion process is complete, Continuous Wavelet Transform (CWT) is applied to reconstruct the fused image from the combined sub-bands. The result is a fused image that contains enhanced features from both input images.

3.5 Fused Image

The final fused image is a composite of Image A and Image B and incorporates both high-level and detailed information from both images. This fused image can then be used for further processing, such as feature extraction and classification for disease detection in potatoes.

4. Significance of the Image Fusion Technique

This fusion technique enhances the quality and detail of the image by leveraging the strengths of multiple imaging modalities. By fusing images at the wavelet level, the resultant image retains both spatial and frequency information, which is critical for the accurate detection of subtle disease symptoms in potatoes.

Image fusion using the Continuous Wavelet Transform (CWT) involves combining information from multiple images to produce a single image that is more informative and suitable for analysis. The fusion rules determine how the wavelet coefficients from different images are combined.

Maximum Selection Rule: The maximum value of the corresponding wavelet coefficients from the input images is selected. High-frequency details are enhanced by this rule.

Minimum Selection Rule: The minimum value of the corresponding wavelet coefficients is selected. Noise reduction can be achieved through this rule.

Mean (Average) Rule: The corresponding wavelet coefficients from the input images are averaged. A balance in the contribution from all input images is maintained by this rule.

Weighted Average Rule: A weighted average of the wavelet coefficients from the input images is computed. This allows one image to be emphasized over the other based on a weight factor.

Absolute Maximum Selection Rule: The coefficient with the maximum absolute value is selected. Significant features from both images are preserved through this approach.

5. Application to Potato Quality Assessment

These image fusion techniques can be applied to potato quality assessment by combining images from different sources, such as visible and near-infrared images, to evaluate quality parameters like texture, color, and moisture content (Bergsma-Vlami et al., 2020).

5.1 Continuous Wavelet Transform

This paper proposes an advanced image fusion technique using Continuous Wavelet Transform (CWT) to enhance disease detection in *Solanum tuberosum* L. (potato) plants (Shahid et al., 2024). The proposed method aims to combine multiple images of potato leaves captured under different conditions (e.g., visible light, infrared) to produce a single, more informative image that can improve the accuracy of disease detection.

5.2 2-D Continuous Wavelet Transform

The 2-D continuous wavelet transform (CWT) represents 2-D data (image data) using three variables: dilation, rotation, and position. Dilation and rotation are real-valued scalars, while position is a 2-D vector with real-valued elements (Shahid et al., 2024). The 2-D CWT serves as a space-scale representation of an image. It could be viewed as the inverse of the scale and the rotation angle, taken together as a spatial-frequency variable, which gives the 2-D CWT an interpretation as a space-frequency representation. For all admissible 2-D wavelets, the 2-D CWT acts as a local filter for an image in both scale and position. Anisotropic wavelets are suitable for detecting directional features in an image. In this paper, feature extraction was performed using the CWT16 fusion method.

The visualization of scalograms provides a comprehensive illustration of the frequency and scale components inherent in diseased potato images. The scalograms of diseased plants exhibit distinct temporal patterns, offering several advantages over raw red, green, and blue (RGB) images. They are valuable in capturing patterns and features at multiple scales and are robust in diverse environmental conditions, being unaffected by lighting conditions. Additionally, they are computationally efficient due to dimensional reduction compared to RGB images. In two dimensions, with time on the horizontal axis and scale on the vertical axis, the scalogram can be displayed (Shahid et al., 2024). Sequentially, the coefficients can be visualized in a 3D contour plot that illustrates the energy coefficient. This has the potential to reveal previously unknown information about the characteristics of non-stationary processes. CWT scalograms are often more suitable due to their ability to capture both spatial and temporal variations in frequency, contributing to the broader field of image analysis and pattern recognition.

5.3 Pseudo Code

Step 1: Read Input Images

image1 = LoadImage('path_to_image1')

image2 = LoadImage('path_to_image2')

Step 2: Apply Best Pre-Processing Method

preprocessedImage1 = PreprocessImage(image1)

preprocessedImage2 = PreprocessImage(image2)

Step 3: Apply Discrete Wavelet Transform (DWT) to Both Images

C1_DWT, S1_DWT = DWT(preprocessedImage1, 'haar')

C2_DWT, S2_DWT = DWT(preprocessedImage2, 'haar')

Step 4: Apply Fusion Rule (Maximum Selection Rule for DWT Coefficients)

FusedDWT_Coefficients = Max(C1_DWT, C2_DWT)

Step 5: Reconstruct Fused Image from DWT Coefficients

fusedImage_DWT = IDWT(FusedDWT_Coefficients, S1_DWT, 'haar')

Step 6: Apply Continuous Wavelet Transform (CWT) to Fused Image

C_Fused, S_Fused = CWT(fusedImage_DWT, 'haar')

Step 7: Detect Diseased Area

diseasedArea = DetectDiseasedArea(C_Fused)

Step 8: Display Diseased Area on Potato Image

DisplayImage(diseasedArea, 'Detected Diseased Area')

5.4 Performance Metric

Entropy is the amount of information contained in a signal. Shannon was the first to introduce entropy as a way to quantify information. The entropy of an image can be evaluated as:

$$H = -\sum_{i=o}^{n-1} p_i \log_b p_i$$

Where n is the number of gray levels (256 for 8-bit images), pi is the probability of a pixel having gray level i, and b is the base of the logarithm function.

Entropy: Higher entropy values indicate richer information content in the fused image. Table 1 shows the entropy values for fused images before and after applying the fusion techniques.

Visual Quality: A subjective measure of the overall quality of the fused image is good.

Artifacts Presence: A subjective measure indicating the level of artifacts present in the fused image.

	Entropy Value	
Image	Before Fusion	After Fusion
Fusedpotato1	6.8880	6.8897
Fusedpotato2	6.0811	6.0821
Fusedpotato3	6.0810	6.0821
Fusedpotato4	6.0819	6.0822
Fusedpotato5	6.9412	6.9432
Fusedpotato6	6.9410	6.9421
Fusedpotato7	6.0809	6.0812
Fusedpotato8	6.0788	6.0813
Fusedpotato9	6.0817	6.0820
Fusedpotato10	6.0920	6.0923

Table 1. Entropy Value

6. Challenges and Limitations

Despite significant progress, challenges remain in disease detection, such as variations in disease symptoms due to environmental factors and the need for large and diverse datasets to train robust models. Studies emphasize the importance of open-access datasets and collaboration between researchers to drive advancements in the field. Furthermore, this study focuses on adapting and combining multiple techniques to create more accurate and efficient disease detection systems for *Solanum tuberosum* L. and other agricultural crops.

7. Proposed Work Findings

7.1 Enhanced Feature Extraction

The fused images obtained through the CWT-based method displayed superior feature extraction capabilities, which are crucial for identifying subtle disease symptoms that may not be evident in individual images.

7.2 Reduction of Artifacts and Noise

The image fusion process effectively reduced noise and artifacts that commonly affect individual images, thus providing clearer and more reliable visual data for disease detection algorithms.

7.3 Practical Applications

The enhanced disease detection capability facilitates early and accurate diagnosis, enabling timely and targeted interventions. This can potentially reduce crop losses and improve yield quality.

7.4 Sample Results

Wavelet = morl

In Figure 3, the top left picture is an image of a diseased potato. The top right image shows the modulus of the diseased potato image. The bottom left image displays the real part of the fused image, the bottom middle image shows the imaginary part of the fused image, and the last image presents the angles of the fused image.

Wavelet = morl

In Figure 4, the top left picture is the potato fused image. The top right image shows the modulus of the potato fused image. The bottom left image displays the real part of the fused image, the bottom middle image shows the imaginary part of the fused image, and the last image presents the angles of the fused image.

Wavelet = wheel

In Figure 5, the top left picture is the potato fused image. The top right image shows the modulus of the potato fused image. The bottom left image displays the real part of the fused image, the bottom middle image shows the imaginary part of the fused image, and the last image presents the angles of the fused image. Figure 5 predicts powdery scab due to the powdery patches on potato tubers caused by *Spongospora subterranea*.

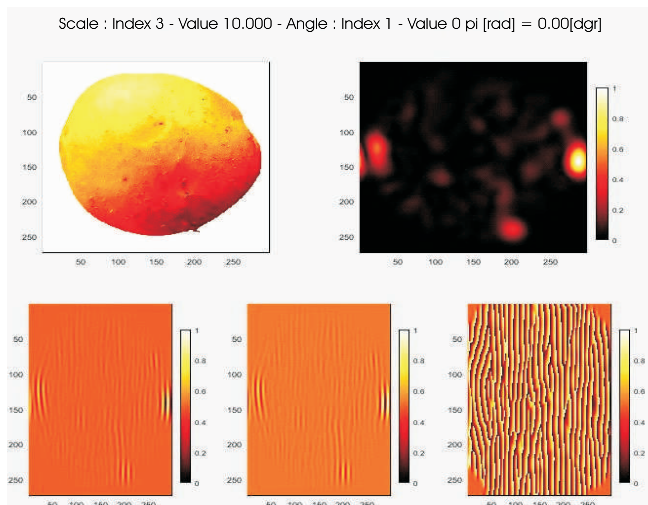

Figure 3. Resultant Diseased Images of CWT Method

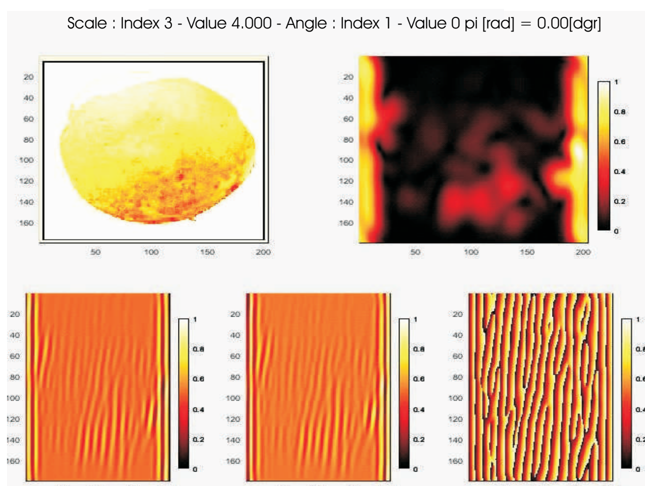

Figure 4. Resultant Fused Images of CWT Method

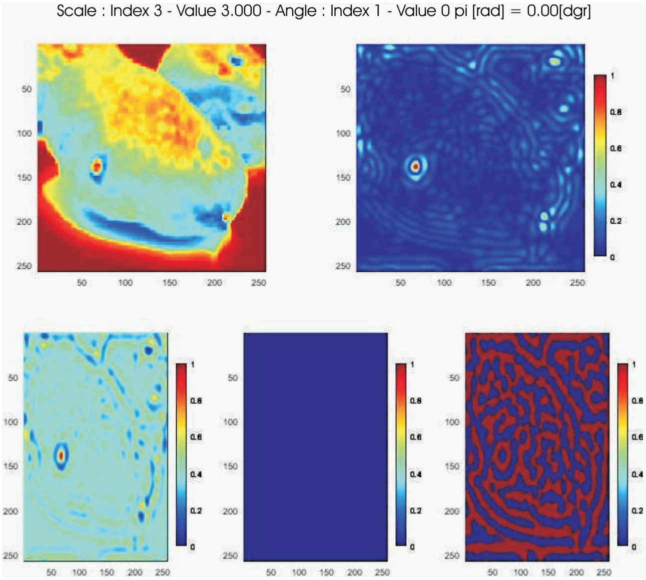

Figure 5. Resultant Fused Images of CWT Method (Powdery Scub)

In Figure 6, the wavelet used is Morlet. The top left picture is the potato fused image. The top right image shows the modulus of the potato fused image. The bottom left image displays the real part of the fused image, the bottom middle image shows the imaginary part of the fused image, and the last image presents the angles of the fused image. Figure 6 predicts Rhizoctonia disease due to the blackening of tubers caused by *Rhizoctonia solani* on potato tubers.

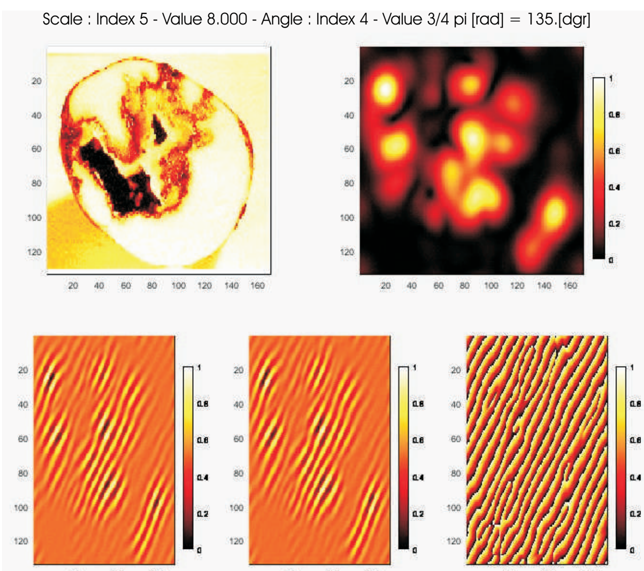

Figure 6. Resultant Fused Images of CWT Method (Rhizoctonia Disease)

In Figure 7, the top left picture is the potato fused image. The top right image shows the modulus of the potato fused image. The bottom left image displays the real part of the fused image, the bottom middle image shows the imaginary part of the fused image, and the last image presents the angles of the fused image. Figure 7 predicts scab disease due to the rough scabby patches on tubers caused by *Streptomyces scabies* on potato tubers.

In Figure 8, the top left picture is the potato fused image. The top right image shows the modulus of the potato fused image. The bottom left image displays the real part of the fused image, the bottom middle image shows the imaginary part of the fused image, and the last image presents the angles of the fused image. Figure 8 predicts Ring Rot disease due to ring-shaped rot caused by *Clavibacter michiganensis* on tubers (Hadizadeh et al., 2019; Waleron et al., 2019). The improved accuracy and reliability of disease detection support better monitoring and management of potato crops, leading to increased productivity and sustainability in agriculture. While this study focused on potatoes, the proposed image fusion technique can be adapted and applied to other crops, broadening its impact on agricultural disease management.

Conclusion

The proposed image fusion technique using Continuous Wavelet Transform (CWT) significantly enhances the

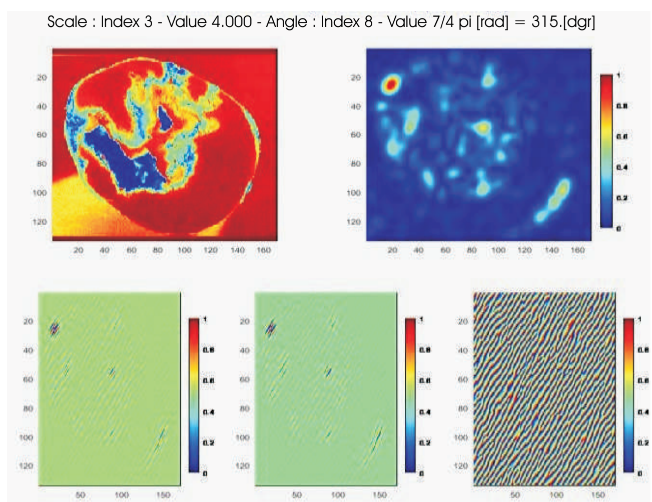

Figure 7. Resultant Fused Images of CWT Method (Scab Disease)

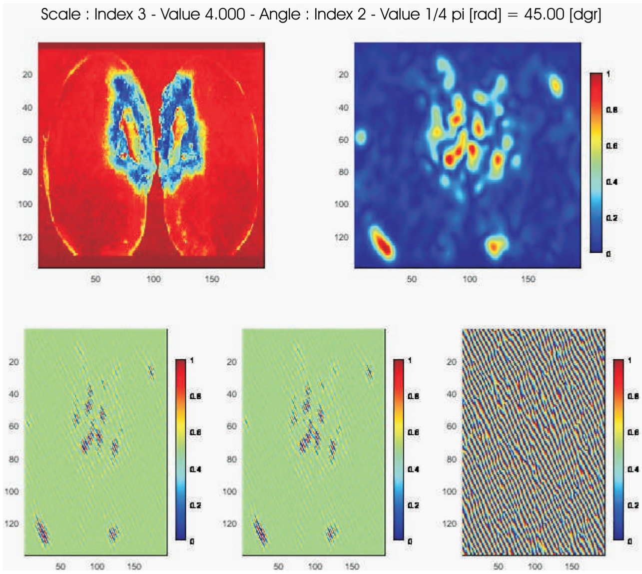

Figure 8. Resultant Fused Images of CWT Method (Ring Rot Disease)

accuracy and reliability of disease detection in *Solanum tuberosum* L. (potato) plants. By leveraging the strengths of multiple imaging modalities, this method provides a powerful tool for early diagnosis and effective management of crop diseases, contributing to the advancement of precision agriculture. Future research will explore integrating the fused images with advanced machine learning algorithms to further enhance disease detection accuracy and automate the identification process. Extensive field testing and validation of the proposed method under various environmental conditions will be conducted to ensure robustness and reliability in real-world scenarios. In the future, the work will be extended to include different angles (45°, 90°, 135°, 180°, 225°, 270°) and radians. Incorporating multi-spectral and hyperspectral imaging data into the fusion process may provide additional insights and further improve disease detection performance.

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