WHEAT LEAF RUST DETECTION BASED ON MULTI-SCALE DWT AND LCS COLOR THRESHOLDING METHODS

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Abstract

Health, Technology, education, and food production are the four main issues facing developing nations like Pakistan, and it is undeniable that agriculture is the most important factor behind economic growth. In addition, implementing a strategy for food production is crucial for citizens to ensure their survival, and it is assumed that these initiatives will result in sufficient farm productivity. One strategy to make a field productive is to take significant care of its components, which starts with cultivating healthy plants or crops. Wheat leaf rust is a fatal condition that attacks young seedlings. It is a significant fungi disease. Leaf rust has 25% effect on the productivity of wheat. To mitigate this issue, a Multi-Scale Discrete Wavelet Transform (MsclDWT) using hybrid fusion rules method is proposed to obtain the complementary information from multiple input images. In second phase, Lab color space followed by color thresholding method is applied to detect and segment wheat leaf rust disease in wheat crop. The proposed model also computes the rust-affected area of the wheat crop, which assists the farmers in the post-medication (anti rust spray) process. The empirical results show that the proposed model achieved 97% of accuracy in rusted pixels detection and classification and outperformed the existing comparative methods.

1. Introduction

Wheat is the world's third most consumed grain, trailing only maize and rice. According to the survey conducted by the United Nations Food and Agriculture Organization (UNFAO), one out of every ten people worldwide suffers from severe malnutrition due shortage of food. In many developing countries, grain yield per hectare is much lower than in developed countries [2]. Agriculture is a key factor of every country's economic growth. Pakistan is an agricultural country, with agriculture employing 65-70% of the population. Crops are visually examined by farmers and agriculture experts. However, such an evaluation process is time-consuming, inefficient, and inaccurate, posing a high risk of loss in the future. Most plants now suffer from viral disease, which has a negative impact on the economic growth of every agricultural country. Rust is caused by hot weather in countries such as Pakistan, Bangladesh, and India. Wheat Leaf Rust is a serious disease that primarily affects young seedlings. This disease appears during the months of February and March when the weather is cold and rainy. Leaf rust reduces wheat production by 25% [1]. Plant disease detection by naked eye is a traditional method that is no longer possible because it requires expert knowledge and is time consuming. Leaf Rust is one of the major fungal diseases in wheat crop. It pustules shows on affected wheat and is small in size, reddish orange in color and appear on the surface of leaf. Pustule can be either gathered on one place or spread on the leaf surface. Figure 1 shows Leaf Rust on a wheat leaf.

Agricultural production is greatly assisted by all these advanced technology, resulting in less waste and higher profits. Timely remedial action and accurate disease diagnosis can have a greater impact on production. Furthermore, it can ensure that the high quality wheat production, resulting in maximum profit for farmers. Image Processing (IP), Computer Vision (CV), Deep Learning (DL), and IoT, are all playing critical roles in the agricultural sector's transformation. [3]. These methods are diametrically opposed to
traditional feature-based supervised learning approaches such as decision tree, random forests, support vector machines, and so on. The detection of leaf rust in remote areas is another motivation for this research. Manually monitoring the entire field takes a long time and a lot of resources due to the density of wheat crops in the field.

The important challenge for leaf rust detection using IP, CV, and DP, is the acquired image background noise and blurriness. The availability of wheat leaf rust disease datasets is the second major challenge. The datasets in [4-5] have issues with illumination, occlusion, bluriness, and angles. Thus, data collection from wheat diseased fields under various conditions is critical for accurate automatic disease identification. The third challenge is the busy background of the wheat crop. It is difficult to separate/segment leaves from the busy background [6-7-8]. Moreover, the appropriate selection of classification and extraction algorithms is also a challenging task [9].

This research work used an unnamed aerial vehicle (drone with camera) to acquire the images of different areas of the wheat crop. However, images acquired using drone have background noise and blurriness problems. To de-noise and reduce blurriness in the acquired image, the model proposed in this study used a Multi-Scale Discrete Wavelet Transform (MsclDWT) using hybrid fusion rules method to obtain the complementary information from input images as a preprocessing step. In second phase, Lab color conversion followed by color thresholding method is applied to detect and segment wheat leaf rust disease in wheat crop. Finally, the affected region's total area is computed. The rest of the paper is structured as follows:

Section 2 covered the fundamentals of wheat rust diseases, as well as relevant studies such as image processing and deep learning models for wheat diseases. Section 3 explains the proposed model. The quantitative/objective quality evaluation metrics were presented in Section 4, and the analysis and results were thoroughly discussed in Section 5. Section 6 concludes the research work.

2. Background Studies

Agriculture is critical to the economy of every country. Wheat has been critical to global food security. It is the world's most widely grown crop, with 217 million has cultivated each and every year [10]. Wheat disease is fungal disease and it is caused from fungi which have no chlorophyll and lack of photosynthesis. Fungi are spread by winds, water, insects, animals and human. Some of that fungal disease are as follow:

i. Leaf rust is called brown rust. The lesion found on the leaf is circular and ellipse shape. Leaf rust infection is found on the upper surface of leaf and base of leaf petiole. It is due to light and spread by wind. It can develop rapidly when temperate is about 20°C and also moisture is available.

ii. Stem rust is also called black rust. It postulates are dark reddish brown in color and found in the both side of leaves. Its spread rapidly when temperate is about 25-30°C with moderate moisture at night.
iii. Stripe rust is yellow rust. The lesion found in leaf sheaths, necks and glum contain yellow to orange yellow in color. This disease occurs when temperature is 10-20°C and rain or dew drops occur. Stripe rust can attack in wheat, barley and other related grass.

iv. Leaf blotch is also called as spot blotch. Lesions caused by this disease are elongated to oval in shape and dark brown in color. The disease is found on the lower surface of leaves.

Figure 2 depicts a visual representation of the diseases mentioned above.

Timely remedial action and accurate disease diagnosis can have a greater impact on production. Furthermore, it can ensure that the high quality wheat production, resulting in maximum profit for farmers. Researchers all over the world are struggling to come up with ideas to assist farmers in making good decisions and take appropriate action. For the last two decades, advancements in technology such as CV and DL have captured the attention of researchers. Researchers have strived to develop effective algorithms for diagnosing wheat diseases and contributed to various aspects of smart agriculture [11]. Numerous IP, CV, and DL algorithms were used to detect and classify crop diseases using leaf images [9-12].

A Grading Diagnosis via Embedded image processing system presented in [13] detect and classify leaf rust using graying processing, edge detection, and median filtering for noise reduction. This method achieved high accuracy rate up to 96%. It fails, however, if the images are acquired in motion and are blurry. The authors of [14] proposed a method that included the following steps. First, the images are captured with a camera, and 1000 of them are saved in a database. To de-noise and de-blur the images, a traditional Median filter is used, and K means clustering is used for image segmentation. Finally, SVM (Support Vector Machine) is used to classify the rust. The idea presented in [15] detect the leaf spot in sugar crop using Jetson GPU Infrastructure. Under daylight conditions, this method produced good results. However, it failed in a real-time scenario where images were captured with a drone camera. In [16], Author proposed to point five diseases in leaf with shape, texture and color features. The proposed system employs SVM, which is unsuitable for large data sets and when there is a lot of noise and image blurriness. Similarly, the research work presented in [17] focus on the detection of disease of pomegranate leaves. K mean clustering and multiclass SVM were used in this study to detect and classify leaf disease. K means clustering algorithm applied to cluster the infected region followed by a simple histogram equalization method is used to enhance the image. Finally, classification is accomplished through the use of the multiclass SVM method. This method achieved the accuracy of 98.07%.

A combination of Convolutional Neural Network (CNN) and K Nearest Neighbor (KNN) was presented in [18] for tomato leaf disease detection. It performed well for high quality enhanced images. However, it fails while detecting disease in busy background images. Its performance also slows down for large datasets training. The research work presented in [19] focused on the deep learning techniques. The first step is to collect data and store it in a database, after which image preprocessing and classification are performed using multiclass SVM. Finally, the KNN method is used to predict whether a leaf is healthy or
unhealthy. This method achieved higher accuracy of 94% for SVM, 96% for CNN, and 82% for KNN. A Machine Learning framework presented in [20] extract features by implementing different algorithms such as Gray Level Co-Occurrence Matrix (GLCM), Local Binary Pattern (LBP), and Shift-Invariant Feature Transform (SIFT). Researchers employed KNN, SVM, and RF model for disease classification. This method achieved 91.24% accuracy. However, it takes long running time and performance needs further improvements. The idea presented in [21] works on color space model. Initially, this method extracts 172 specific points from the input images and SVM model was trained using these extracted points. This method achieved higher accuracy of 94%. However, it fails while working with busy background images and has spectral distortion problem.

A region categorization based framework was proposed in [22] achieved maximum accuracy of 98.63% using single camera image. Initially, morphological method is used to de-noise the image and then k (k-FLBPCM) method was used to extract the interesting points. Finally, SVM model was trained using these extracted points. The accuracy of this method degraded frequently using busy background images or images with background noise and blur (image acquired using drone technology). A ML based method was introduced in [23] extracts spatial features (key points) using Directional Local Quinary Patterns (DLQPs) and same SVM model was applied for diseases categorization. This method performed well in terms of accuracy, but its detection of rusted pixels in busy background images still needs to be improved. Deep learning technique for the identification and recognition of disease in the cereal crops was proposed in [24]. In this paper, eight major kind of cereal covering 56% of the major world are taken in consideration. Various ML, IP, CV, and DL methods were assessed for different types of crop diseases in simple and complex background images. A framework presented in [25] used prominent DL networks such as ResNet 50, InceptionV3, and VGG19. The researchers compared the results of all these networks on a single dataset contains 1500 images representing three types of leaf diseases. The images were acquired using camera technology in Ethiopia. The dataset is freely accessible to the public. VGG19 outperformed all other networks in terms of accuracy. A residual neural network was proposed [26] for the of 1200 stripe rust images. The ResNet model was trained using the 224×224 PX training patches from the database. This method achieved high classification result accuracy of 77% for camera images. However, it failed to de-noised and de-blur the motion images. A fusion method for crop disease detection was proposed in [27]. Decimation of Plant village dataset having total of 54,308 images and digipathos dataset having total of 43,106 images are done on the GLCM and Gabor filter for feature extraction. This method achieved high accuracy. However, fusion model is not suitable for the complex background images.

This research work proposed a Multi-Scale Discrete Wavelet Transform (MsclDWT) using hybrid fusion rules method is proposed to obtain the complementary information from input images. In second phase, Lab color conversion followed by color thresholding method is employed to detect and segment wheat leaf rust disease in wheat crop. The proposed model also computes the rust-affected area of the wheat crop, which aids in the post-medication (anti rust spray) process.
3. Materials And Methods

3.1. Data Collection

The proposed method for wheat disease detection and classification is presented in this section. Wheat leaf rust affected and normal images are gathered from several wheat fields in the first step, and a new database is generated using those images. There are some open access online plant datasets available, such as plant village datasets, which contain over 40000 images of various plants. However, there aren't enough images of wheat leaf rust disease. Thus, over 2000 wheat crop images for two distinct classes (Healthy and rusted) of wheat leaves are collected from Pakistan's actual field (City Bannu) in 35° C. We did not collect these images with a standard camera or a smart phone, but rather with an unnamed aerial vehicle (drone with camera) over various areas of the wheat crops. As discussed earlier that manual monitoring of the entire field takes a long time and a lot of resources due to the density of wheat crops in the field and it is impractical to acquired images of the leaves manually by hand. Therefore, we used drone technology to capture all of these images. Figure 3 shows healthy and unhealthy (leaf rust) samples.

3.2. Proposed Method

To reduce background noise, blurriness, and spatial distortion, we took two images of each scene and employed a Multi-Scale Discrete Wavelet Transform (MsclDWT) using hybrid fusion rules method to extract complementary information from the input images. Figure 4 visually shows the MsclDWT method. First and foremost, the input images are decompose to obtain its coefficients using proper fusion rules. To process wavelet coefficients, it is important to applied suitable decomposition scales and wavelet family. Few scales selection causes loss of image information while too many scales selection causes in image blurriness. This study employed a four-level scale for decomposing high frequency components and a two-level scale for decomposing low frequency components, as well as the 'Haar' family. In this study, Principal Component Analysis (PCA) and Consistency Verification functions are employed as a fusion rules. After that, Inverse DWT is applied to get the final fused image. These steps/rules are applied to get complementary information/features. PCA is used in the image fusion process to highlight the silent details in the input images. It is applied to calculate the weights of the coefficients using the following equations.

1) Suppose input modalities coefficients are $W^1$ and $W^2$.

\[
W^1 = \begin{pmatrix}
Z^1_1 \\
Z^1_2 \\
\vdots \\
Z^1_n
\end{pmatrix} \quad W^2 = \begin{pmatrix}
Z^2_1 \\
Z^2_2 \\
\vdots \\
Z^2_n
\end{pmatrix}
\]  

(1)
2) Covariance matrix measurements

\[ CVN(W^1, W^2) = E \left[ (W^1 - \mu_1)(W^2 - \mu_2) \right] \]

Where \( E \) denotes expectation vector and \( \mu_1, \mu_2 \) are the coefficients which can be calculated using Eq. (3).

\[
\mu_1 = \frac{1}{n} \sum_{a=1}^{n} Z_i^1
\]

\[
\mu_2 = \frac{1}{n} \sum_{a=1}^{n} Z_i^2
\]

Then Eigen vectors (VCc) and Eigen values (Edv) are calculated using Eq. (5).

\[
[VCcEdv] = eig(CVN)
\]

VCc is calculated to obtain normalized weights using equations (6).

\[
Ri_1 = \frac{VCc(1)}{\sum \sum VCc}, Ri_2 = \frac{VCc(2)}{\sum \sum VCc} \quad (6)
\]

At the end, fused coefficient can be calculated using Eq. (7).

\[
W_F = W^1 \times Wi_1 + W^2 \times Wi_2
\]

And then Consistency Verification is fusion rule is used to reduce errors/wrong pixels values. Here a window size of 9X9 is applied to generate a new mapping window for decision purposes. Following this step, the final image has all complementary information/features.

In the second step, Lab color conversion followed by color thresholding method is employed to detect and segment the normal and rust affected images. Image conversion is a subset of preprocessing that involves converting images into fewer color spaces such as lab space or black and white in order to simplify the computational process. However, conversion is not always necessary; it should if it should be avoided when the result of the conversion may affect the spatial and spectral information. Lab color space can be defined mathematically in three axes, where L denotes lightness, “a*” represents the color information of a green-red axis, and “b*” represents the color information for a blue-yellow axis. The important feature of Lab color space is its device independence, which means that colors are defined independently based on the nature of creation. In this study, the RGB values are first converted into a Lab
color space model to simplify the computational process and improve the accuracy of rusted pixel detection. The Lab color model comes with a variety of benefits, including device independence and a broad color gamut. Furthermore, it can compensate for the RGB color model's uneven color distribution, which contains an abundance of transition colors from blue to green. Image is converted to lab space for further process of segmentation. The advantage of lab space image is by having 1 channel dedicated to the luminosity of the image and 2 other dedicated to color information. Lab color space is more accurate color space because it allows you to do things you cannot so with RGB color image. It also reduce color which is easy to perform further processing. Figure 5 depicts lab color space converted image.

Finally, Lab color space method is followed by color image thresholding to segment and classified the rusted pixels. The segmentation process is based on different information found in the image. This might be boundaries, color information, and segment of an image. The image background is removed based on whether the image pixel falls above or below the threshold value. It will cause to separate images with a specific end goal to remove the healthy part from wheat leaf, which will break down the infection. We have used color thresholding technique which will convert the unhealthy or rust part of leaf pixel value to 0 and healthy part will be in the same color. It is better for huge measure of information and gives better and accurate result with less time. Equations (8), (9), and (10) have been developed to measure the thresholding values for the yellow color using the minimum and maximum values of the RGB components. The original values, however, have been modified to accommodate a 10% difference [28].

\[
g_{\text{gray}}(m, n) = \begin{cases} 
  \frac{f(m, n)}{\text{gray1}(m, n)}, & 0 \leq \text{red}(m, n) \leq T_{rr}, \\
  \text{gray1}(m, n), & \text{red}(m, n) > T_{rr}.
\end{cases}
\]

8

\[
g_{\text{gray}}(m, n) = \begin{cases} 
  \frac{f(m, n)}{\text{gray1}(m, n)}, & T_{rrg} \leq \text{green}(m, n) \leq 1, \\
  \text{gray1}(m, n), & \text{green}(m, n) > T_{rrg}.
\end{cases}
\]

9

\[
g_{\text{gray}}(m, n) = \begin{cases} 
  \frac{f(m, n)}{\text{gray1}(m, n)}, & 0 \leq \text{blue}(m, n) \leq T_{rrb}, \\
  \text{gray1}(m, n), & \text{blue}(m, n) > T_{rrb}.
\end{cases}
\]

10

Where gray1(m,n) is the intensity value of pixel and red(m,n), green(m,n), and blue(m,n) are the intensity value for red, green, blue channels. We keep the minimum threshold 0.058 and maximum 99.617 for channel 1, minimum 0 and maximum 14.601 for channel 2, and minimum 0 and maximum 43.442 for channel 3. Then separated background image and converted the segmented image in to binary one that is rust part of the leaf will convert to 1 and background to 0. Moreover, the rust affected area are computed by summing all pixels having intensity value of 1 i.e. rust affected pixels.

4. Results
The performance of our proposed model will be discussed in detail in this section. The experiments were carried out with MATLAB 2020a running on a Core i7 4780 CPU with 1.7GHz and 16GB of RAM. The qualitative and quantitative both methods were used to evaluate the accuracy and performance of our proposed model. Performance evaluation metrics used in this research are as follow:

### 4.1. Structural Similarity Indexed Measures (SSIM):

SSIM computes the similarities between original and fused image. This research work select this evaluation metric to assess the difference and complementary information between input images and fused image. Better fusion outcomes are associated with higher SSIM values. The SSIM evaluation metric is depicted in Eq. 11.

\[
SSIM = \frac{2\mu_{IMG_{or}}\mu_{IMG_{fsd}} + c_1}{\mu_{IMG_{or}}^2 + \mu_{IMG_{fsd}}^2 + c_1} \frac{2\sigma_{IMG_{or} IMG_{fsd}} + c_2}{\sigma_{IMG_{or}}^2 + \sigma_{IMG_{fsd}}^2 + c_2}
\]

### 4.2. Peak Signal to Noise Ratio (PSNR)

PSNR Computes intensity levels between original and fused image. The selection of PSNR is based on the intensity values variation among the original input images and fused image. Better fusion outcomes are associated with higher SSIM values. The PSNR evaluation metric is depicted in Eq. 12.

\[
PSNR = \frac{(255)^2}{M \times FSD \sum_{m=1}^{M} \sum_{fsd=1}^{FSD} (IMG_{or}(m, fsd) - IMG_{fsd}(m, fsd))^2}
\]

### 4.3. Sum of Correlation Difference (SCD)

SCD Computes the transmitted information from source images to the fused one. Its value must be high. Eq. 13 shows the SCD evaluation metric.

\[
SCD = corl2 (fsd - img_1, img_2) + corl2 (fsd - img_2, img_1)
\]

The empirical results of our proposed Multi-Scale Discrete Wavelet Transform (MsclDWT) method achieved better results than [2–13–17–26]. Figure 6 depicts the qualitative results of our proposed (MsclDWT) method.

The qualitative results clearly shows that our proposed method has acceptable results. A single image captured with camera technology can be used directly for post-processing, and deep learning algorithms can be used to segment and classify the normal and affected images. However, this approach is
impractical because we cannot evaluate the rust affected area in the entire crop field with a single image. This study used drone technology to acquire 2 or 3 images of the same scene and fused it using the proposed MsclDWT method to get the complementary information of all images. The empirical results show that existing systems fail during their evaluation with busy background images. Table 1 shows the quantitative results of the recent studies presented in [2–13–17–26] and our proposed method.

Table 1

<table>
<thead>
<tr>
<th>Study &amp; Year of Publication</th>
<th>SSIM (Single Image)</th>
<th>PSNR (Single Image)</th>
<th>SCD (Single Image)</th>
<th>SSIM (Busy Background Image)</th>
<th>PSNR (Busy Background Image)</th>
<th>SCD (Busy Background Image)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed MsclDWT</td>
<td><strong>7.9874</strong></td>
<td>32.8412</td>
<td><strong>25.0124</strong></td>
<td><strong>11.2541</strong></td>
<td><strong>33.2147</strong></td>
<td><strong>24.2357</strong></td>
</tr>
</tbody>
</table>

Table 1 presents that our proposed method has achieved better results than the rest of the studies. It was observed that the rest of the studies performed well for a single image. However, it fails to extract features from a busy background image with multiple leaves. Figure 7 shows the qualitative results of Lab color space method.

Figure 8 depicts the segmentation and classification qualitative results of existing and proposed methods for single image acquired by camera and Fig. 9 shows the qualitative results of existing and proposed methods for busy background crop field image acquired by drone technology.
From Figs. 7 and 8, it was observed that our proposed method outclassed the methods presented in [17–26] in all cases. Furthermore, the results achieved form comparative methods were severely degraded using busy background crops acquired images. Table 2 shows the results of the existing and proposed methods for detecting rusted pixels as well as their running times.

Table 2
Rusted pixels miss detection

<table>
<thead>
<tr>
<th>Single image</th>
<th>Busy background image</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Image 1</strong></td>
<td></td>
</tr>
<tr>
<td>Methods</td>
<td>Miss Detection</td>
</tr>
<tr>
<td>Mangena, V., et al. [17]</td>
<td>801</td>
</tr>
<tr>
<td>2021</td>
<td></td>
</tr>
<tr>
<td>Schirrmann M., et al. [26]</td>
<td>709</td>
</tr>
<tr>
<td>2021</td>
<td></td>
</tr>
<tr>
<td>Proposed Method</td>
<td>849</td>
</tr>
</tbody>
</table>

| **Image 3**  |                       |
| Methods      | Miss Detection        | Running Time (Sec.) | Miss Detection | Running Time (Sec.) |
| Mangena, V., et al. [17] | 712 | 4 | 09 | 5 |
| 2021         |                       |                 |                |                   |
| Schirrmann M., et al. [26] | 755 | 5 | 13 | 6 |
| 2021         |                       |                 |                |                   |
| Proposed Method | 804 | 4 | 28 | 5 |

Table 2 showed that our proposed method performed well in terms of single image analysis. However, when calculating rusted pixels using busy background images, it completely outperformed the existing comparative methods.

**Conclusion**

This article proposed a model for wheat diseases based on transformation and machine learning algorithms. To evaluate the proposed system, we captured images of wheat leaves (normal and rusted) using drone technology from various fields in Bannu, KPK, Pakistan. First and foremost, MsclDWT using
hybrid fusion rules method was proposed to obtain the complementary information from input images. In second phase, Lab color conversion followed by color thresholding method was applied to detect and segment wheat leaf rust disease in wheat crop. Our proposed method was analyzed using single and busy background crop field images. The proposed model also computes the rust-affected area of the wheat crop, which assists the farmers in the post-medication (anti rust spray) process. The empirical results showed that the proposed model achieved 97% of accuracy in rusted pixels detection and classification. Finally, the proposed model also computes the rust-affected area of the wheat crop, which assists the farmers in the post-medication (anti rust spray) process.

In the future, we hope to expand our dataset and will include more wheat diseases images. Moreover, our goal is to implement our model on server based system. Another future plan is to deploy our model on smart mobile devices to assist farmers at early stages.

Declarations

CONFLICT OF INTEREST:

The authors has no conflict of interest.

DATA AVAILABILITY STATEMENT:

The datasets generated and/or analyzed during the current study are not publicly available. However, datasets may be provided by the corresponding author on reasonable request.

References


**Figures**

![Figure 1](image-url)
Rust affected leaf

(a) Leaf Rust  (b) Stripe Rust  (c) Stem Rust  (d) Leaf Blotch

Figure 2

Wheat leaf diseases

Figure 3

Wheat leaf leaves samples
Figure 4

MsclDWT proposed method

Figure 5

Lab color space conversion
Figure 6

Proposed MsclDWT fusion results (a) input single image 1, (b) input single image 2 of the same scene, (c) MsclDWT fused image, (d) input busy background crop image 1, (e) input busy background crop image 2 of the same scene, (f) MsclDWT fused image
**Figure 7**

Lab color space results (a) input normal image, (b) result of (a) having no white color, (c) input rusted single image, (d) result of (c) with white color shows rusted pixels, (e) input busy background crop image, (f) result of (e) with white color shows rusted pixels, (g) input busy background crop image, (h) result of (g) with white color shows rusted pixels
Figure 8

Color thresholding using single camera image (a) input camera image (b) result of [17], (c) results of [26], (d) proposed result, (e) input camera image, (f) result of [17], (g) result of [26], (h) proposed result.
Figure 9

Color thresholding using single camera image (a) input camera image (b) result of [17], (c) result of [26], (d) proposed result, (e) input camera image, (f) result of [17], (g) result of [26], (h) proposed result