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DISEASE DETECTION IN TEA LEAVES USING IMAGE PROCESSING

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ABSTRACT

Plant disease detection plays a vital role in achieving more quantity and better quality of agricultural product. Leaves are considered to have various characteristics, which help in detecting diseases in plants. Finding these diseases is a tedious task, which can be accelerated using image processing techniques. Image processing includes various feature extraction methods that can be used to find abnormalities in leaves. Prior steps for this involve extraction of features like color, texture and shape, from leaf image. Appropriate classification algorithm can be used to train and test the system using extracted features. This paper proposes the detection of disease in Tea leaves. Disease in tea plant is a serious issue which can have a direct impact on its production loss. By using HSV-Gabor filter for texture extraction, SIFT for detecting deformation in its shape in MATLAB and Probabilistic Neural Network Classifier (NNC) for training of the system, these diseases are classified.

KEYWORDS: Leaf Disease Detection, Colour Extraction, HSV, Image Processing. Texture Feature Extraction, Gabor Filter, Shape Feature, SIFT, Classification, Probabilistic Neural Network.

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INTRODUCTION

Tea plant cultivation is usually done in large commercial operation. Tea is a very demanding beverage all over the world. India is one of the largest tea producing country in the world. From Assam and Darjeeling in east to Tamil Nadu, Kerala and Karnataka in south, the production of Tea is spread and is used for exportation in various countries, resulting in economic growth. So it becomes utmost concern of Government to take care of quality and quantity of production as it will affect the revenue. As a result, researchers are working in direction of decreasing the production loss caused due to various diseases in Tea plant. There are various types of diseases found in tea plant depends on causing source such: Camellia dieback and canker, Camellia flower blight, Root rot, Algal leaf spot, Blister blight, Horse hair blight, Poria root disease (Red root disease),Tea scale Aphids (Tea aphid),Spider mites (Two-spotted spider mite).The tea plant is subject to attack from at least 150 insect species and 380 fungus diseases. In northeast India, where 125 pests and 190 fungi have been detected, losses from pests and diseases have been estimated at 67 million pounds (30 million kg) of tea per annum [12]. Fungal diseases are more common in plants in hilly areas and a lot of work is done in detection of this type of diseases[14]. This paper gives an idea about how to detect such diseases in Tea plant using its leaves.

LITERATURE SURVEY

A framework for programmed recognizable proof of medicinal plant leaf from the given database is proposed and actualized. The shades of the leaf, limit based components and minute elements are utilized for recognizing leaf assortments. Another technique is distinguishing the leaf utilizing Gabor channel. In this strategy leaf, pictures are characterized into various classes[1]. Plant leaf pictures of three plant sorts are dissected by changing the channel parameters[2]. The utilization of the shading highlights for separating ailment results in the better result. Dissecting pictures in HSV structure give more data than in RGB form[3]. The Probabilistic Neural Network (PNN) with picture and information preparing procedures is likewise utilized for actualizing a universally useful mechanized leaf acknowledgment framework for plant classification[4]. Poorly textured articles containing tubular and void parts can be perceived, in jumbled scenes under subjective review conditions and build up various novel segments. To start with, present another edge-based nearby component indicator that is invariant to connection changes. The elements are situated on edges, and an area is assessed on a scale unvarying way. Second, the foundation mess does not influence the area descriptor registered for frontal area highlights, regardless of the fact that the element is on an article limit[5]. A component in leaves is additionally separated, which is called as 'Form'. It depicts the lines amidst the centroid and every shape point on a picture. A length histogram is made to demonstrate the dispersal of separations in the leaf contour[6]. The shading and surfaces, shape and vein, elements were incorporated to characterize a leaf, a classifier called Probabilistic Neural system (PNN) was used[7]. One other strategy comprises of four primary strides, in the initial step the info RGB picture a shading change structure is made, and afterward concealing of the green pixels and evacuation of those pixels by applying particular limit esteem, sought after by the division process[8]. For the helpful portions, the composition measurements are processed; at long last the separated elements are gone through the classifier. By revising picture geometric twists utilizing mapping capacity, with a specific end goal to procure the directions of quadrangle corner focuses in the warped picture; Hough change is abused. At that point, by utilizing edge technique, picture division was performed. To wipe out the impact of openings in the leaf, another shape extraction methodology was introduced. Pixels are filtering from one side to inverse side in four headings to separate an article forms. Next, form locale was filled. At last, by utilizing pixel number, measurement leaf territory was measured. In addition, other vital parameter, leaf edges, can likewise be gotten utilizing this strategy. This strategy was tried with some live leaf pictures. Exploratory results demonstrate this technique can quantify the plant leaf region accurately[8]. There is another technique, which is utilized for the recognition of plant infections by applying it on their leaves' pictures. Picture securing, pre-handling, analyzation, highlight extraction and classification are the strides included in the Disease identification strategy[11]. The Gabor Wavelet changes can remove both the time (transient) and recurrence data from a given sign, and the modifiable size of piece permits it to perform multi-determination examination. Between sorts of wavelet changes, the Gabor wavelet has been utilized as often as possible for picture processing[14].

METHODS

1. Feature extraction

i. HSV colour space for colour feature extraction[3]

HSV stands for hue, saturation, and value, and is also called HSB (B for brightness). Observing and classify colours in given clustered data points, in HSV colour model is easier than in other colour models. The data points in the hue-axis do not deviate much from one concentration to the next, and it fits the numerical range of colour given and only in the saturation-axis that the displacement of the cluster of data points is visible. The colour information on the saturation axis increase as the level of concentration decreases. It is observed that it is easier to get more colour information in the HSV representation than compared to RGB representation.

CONVERSION FROM RGB TO HSV

cmap = rgb2hsv(M)
hsv_image = rgb2hsv(rgb_image)

ii. Texture feature extraction using Gabor Wavelet

Gabor wavelet provides a mean for better spatial localization. A Gabor function is defined as the product of Gaussian kernel times and complex sinusoid. The Gaussian function is called as the envelope, and the complex sinusoid is called the carrier. The features calculated by the mean and variance of the Gabor filtered images. A feature vector is generated for an image, for example, if a 4×9 Gabor wavelet set is used, and then there will be 72 elements in this feature vector, which will be calculated by normalizing maximum magnitude in each feature vector set.

A 2-D Gaussian curve having spread of σ in both t and z direction can be represented as

$$g(t,z,\sigma)=\frac{1}{2\pi\sigma^2}\exp(-(z^2+t^2/2\sigma^2))$$

The complex sinusoid is explained as follows, where v represents special frequency, θ denotes orientation and $\emptyset$ denotes the phase shift $(i=\sqrt{-1})$.

$$s(t,z,v,\theta,\emptyset)=\exp\{i2\pi(t.v\cos\theta+z.v\sin\theta)\}$$

This Gabor function can be shown as

$$h(t,z,\sigma,v,\theta,\emptyset)=g(t,z,\sigma).s(t,z,v,\theta,\emptyset)$$

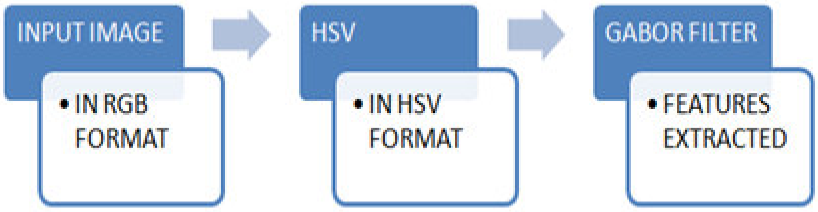


Figure 1
Firstly, Input Image is given in RGB format which is converted into HSV format and then given as input to GABOR Filter for COLOR- TEXTURE feature extraction

iii. Scale Invariant Feature Transform

The image descriptor Scale Invariant Feature Transform (SIFT) is used for image-based matching and recognition. (MATLAB code developed by David Lowe) The set of descriptors are used for a wide variety of purposes in computer vision applications, which are related to point matching between different views of a 3-D scene and object recognition. The SIFT image descriptor is invariant to various parameters of image like translations, rotations and scaling transformations. They are also robust to mid-range perspective transformations and illumination variations. Practically, the SIFT descriptor has been proven to be extremely resourceful in practice for image matching and object recognition in real-world conditions.

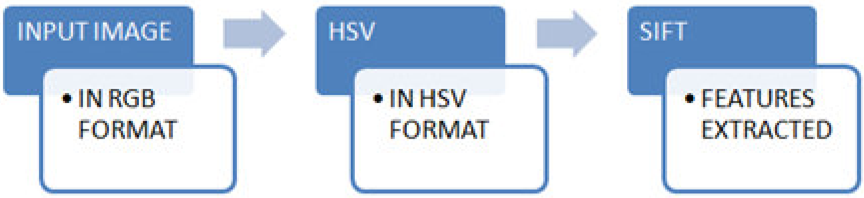


Figure 2
Depicts extraction of Scale Invariant Features from an image

In its basic version, with the intention that SIFT descriptor should be used for matching corresponding interest points between different images, the SIFT descriptor contained a method for detecting interest points from a grey-level image for summarizing description of the local image structures with the help of statistics of local gradient directions of image intensities that were accumulated to give a in a local neighbourhood around each interest point. The SIFT descriptor also gives better performance for tasks such as object classification, texture classification, image alignment and biometrics when applied to dense grids (dense SIFT). Different level scaled images will be used for calculating one Difference of Gaussian abbreviated as (DoG). Once these DoG's are found, images are searched for local extremes over scale and space. For e.g., one pixel in an image is compared with its eight neighbours as well as nine pixels in next scale and nine pixels in previous scales. If it is a local extreme, it can be a potential key point. It basically means that the key point is best represented in that scale. Local extreme is local maximum or local minimum value of pixel.

2. Classification

The features extracted from HSV-Gabor and SIFT are applied to Probabilistic neural network (PNN), which is used to map any input pattern to number of classifications. PNN can be forced into a more general function approximator.PNN has its origin in the statistical algorithm called kernel discriminant analysis. This algorithm organizes operations into a multilayer feed forward network with following four layers.

a. Input layer
b. pattern layer
c. Summation layer
d. Output layer

PNN inherits parallel structure. Orders of magnitude are faster than back-propagation neural network therefore training process is faster in PNN. This algorithm does not need extensive re-training for adding or removing training samples. As size of training set increases PNN is guaranteed to converge to an optimal classifier. PNN can also overcome local minima issues caused in other neural networks.PNN can begin to generalize new patterns as soon as a single instance of a pattern representing particular category is observed. The generalization criterion is refined as more number of patterns are observed and recorded in PNN.

RESULTS AND DISSCUSSION

Tea Leaf Datasets

Following images in figure 3 named as image a, b, c, d, e, f, and g are input images of tea leaves to the disease detection system. Disease spots are visible to human eyes in various images. Our aim is to detect these disease spots with the help of image processing algorithm used in the automated system. Image (a) represents the algal tea spot. Image (b) shows the tea leaf affected by the disease Twig Dieback and Stem Canker. Image (c) denotes the effect of Brown Blight disease on the tea leaf. Affected edges of tea leaf can be observed in image (d) and image (e) which are caused by the diseases Blister Blight, Brown Blight respectively. At the last image (f) shows different Brown and Grey Blight in the same tea leaves.

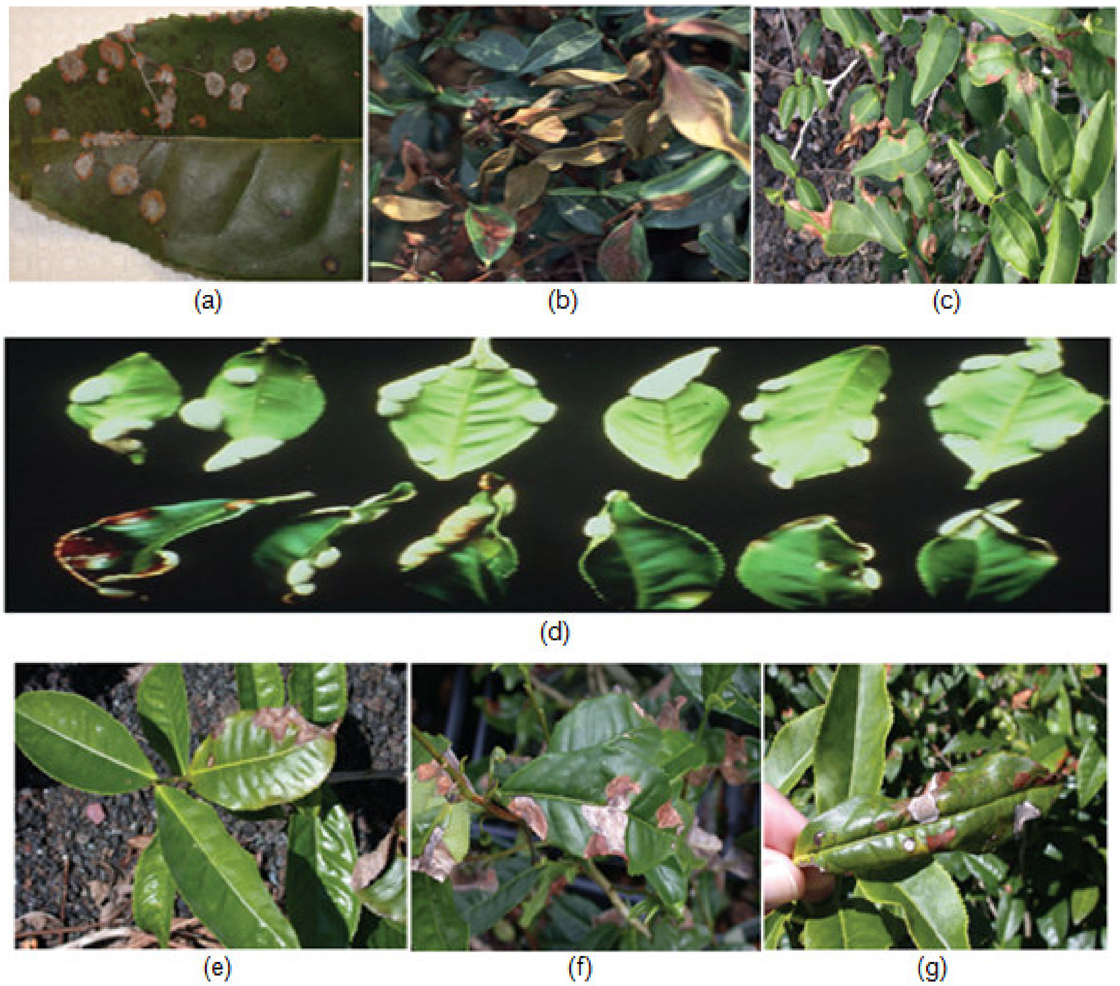
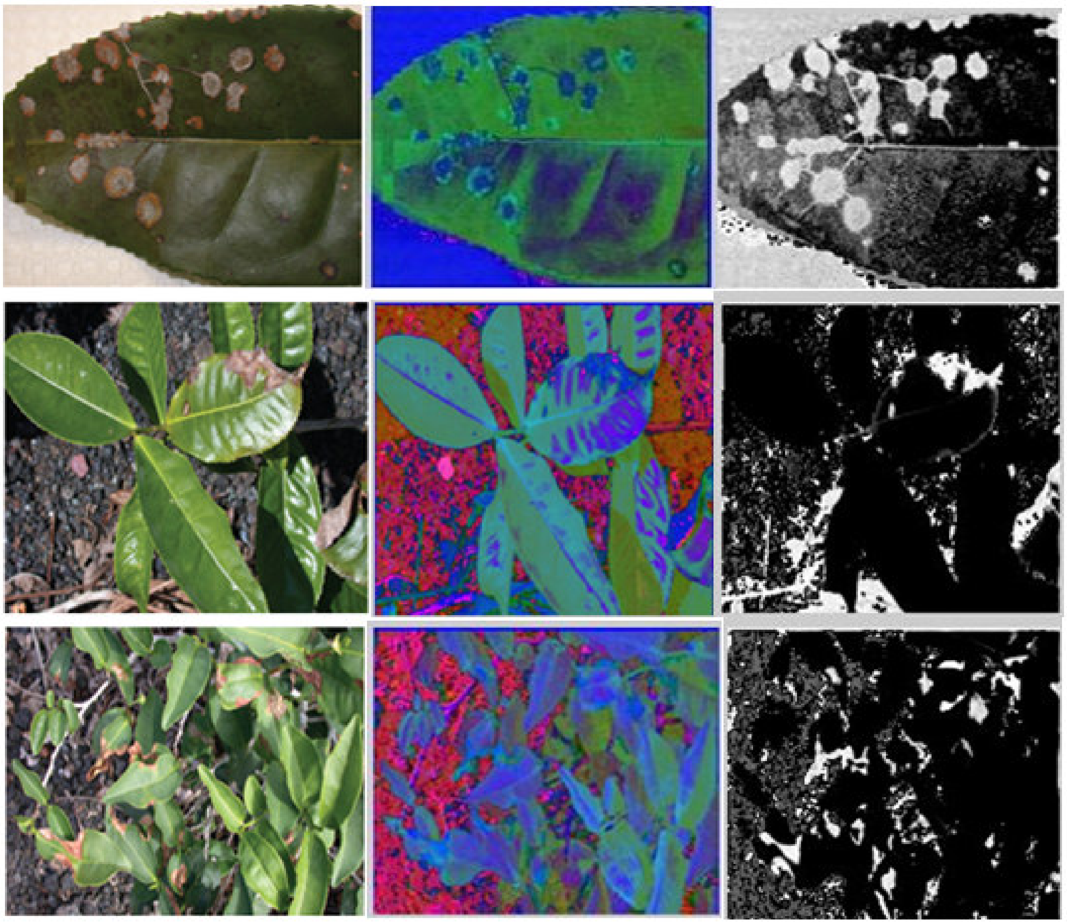


Figure 3
Tea Leaf Datasets with various kinds of diseases a). Algal Tea Spot, b). Twig Dieback and Stem Canker, c). Brown Blight many, d).Blister Blight, e). Brown Blight f)and g) shows different Brown and Grey Blight in same leaves

Results of Texture Features extracted by HSV-GABOR Filter

Figure 4 shows the results of application of HSV and Gabor wavelet filter to input data set of tea leaf images. First column (a) of the figure shows the input leaf image. Second column (b) represents the various colour clusters form due to application of HSV colour model. The disease affected spots on the leaf are highlighted by dark blue shade whereas remaining healthy leaf part is characterised as fade green tint. Some images also contain noise caused by the shadow captured in the image. Third column(c) in the figure 4 represents the output images after the application of Gabor wavelet filter. While HSV colour model highlights the various colour clusters in the image, the Gabor filter provides better means of spatial localization. That is Gabor filter enables us to study and analyse the texture of disease affected spots .It also filters out the noisy part caused in HSV model and clearly distinguishes the disease affected parts from rest of the healthy leaf area.



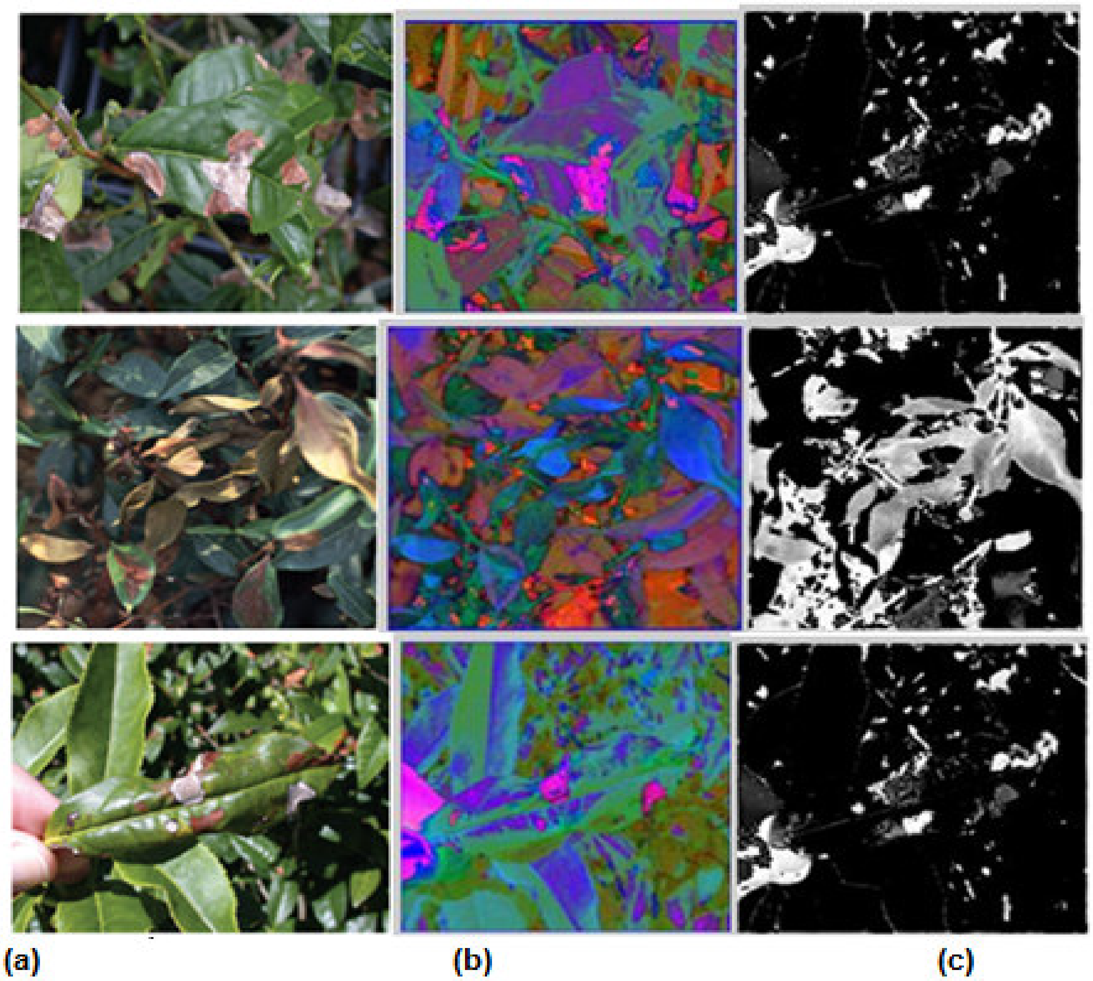


Figure 3
a).Shows the Leaf Datasets b).Shows Color Feature Extraction in leaf using HSV which highlights the disease spots with purple color c). Leaf after Extraction of Texture Feature using Gabor Filter.

Results of Shape Analysis

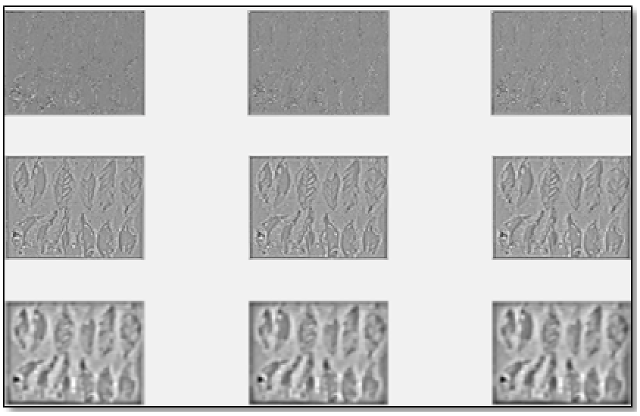


Figure 5
Shows the intermediate output of SIFT giving shape features to identify Blister Blight

Figure 5 above represents the intermediate output of SIFT for one of the input image giving shape features to identify Blister Blight. Scale Invariant Feature Transform is used here to analyse the texture of disease affected edges of the tea leaf. Given an input image SIFT works on different scales and orientations of the image to highlight the disease affected areas on the tea leaf boundary. Figure 6 below shows the Final results of the SIFT method. The green and blue key points ('+') denotes the unhealthy parts on tea leaf boundary for two different SIFT configurations.

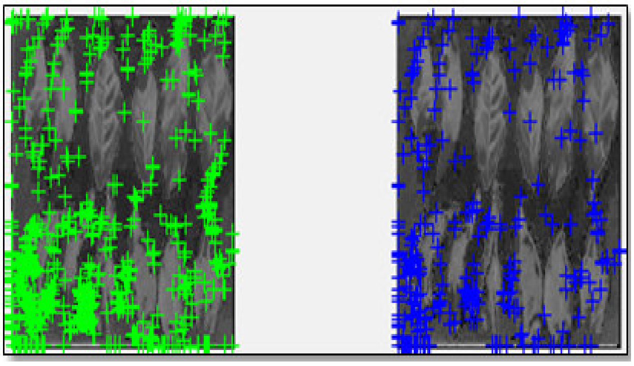


Figure 6
Shows the selected key points, representing the diseased sections of leaf (d) in figure 3

Thus we have used HSV and Gabor wavelet for detecting diseased spots in the interior area of the tea leaf while we have used SIFT method to detect disease defected edges of the tea leaf.

CONCLUSION

On the basis of results obtained from the above method, we are able to spot diseased areas in the tea leaves by extracting its features. Further by training the system using Neural Network Classifier, we are able to detect the percentage of affected area

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