IJETIR

ISSN (Online) 2583-0554

International Journal of Emerging Technologies and Innovative Research (IJETIR)

Volume 5, Issue 7, July 2025

Impact Factor: 5.731

Correlation Analysis of Banana Leaf Colour and Texture Features with Chemically Determined Nutrient Concentrations

Phadke Dhanashri Ashok[1] and Dr. Nidhi Mahawar[2]

Research Scholar[1], Associate Professor[2]

Jayoti Vidyapeeth Women's University, Jaipur, Rajasthan, India[1, 2]

Abstract: *Proper plant nutrient status evaluation is critical to enhancing plant productivity, fertilizer-use efficiency and sustainable agriculture. The commercial importance of bananas (Musa spp.) makes it essential to ensure that it is well balanced in mineral nutrition for optimal vegetative growth, photosynthetic performance and fruit development. Traditional nutrient evaluation is based on the chemical analysis of plant tissues in the laboratory, and it supplies quantitative data but is destructive, requires special equipment and analytical costs. A non-destructive method for examining visible leaf properties related to nutritional differences is digital image analysis. The present paper suggests an integrated analytical framework to explore the correlations between the banana leaf colour and texture features, and the chemically determined concentrations of N, P, K, Mg and Fe. The digital leaf images are represented by red–green–blue (RGB), hue–saturation–value (HSV), and CIELAB colour models and spatial texture characteristics are quantified by descriptors of grey-level co-occurrence matrix (GLCM), such as contrast, correlation, energy, and homogeneity. The analytical scheme proposed includes the use of standardized image acquisition, colour calibration, leaf segmentation, determination of nutrients in the laboratory, Pearson and Spearman correlation analysis and multivariate statistical modelling. Concern is given to the identification of optical features related to leaf chlorosis, pigmentation variability and tissue heterogeneity. A set of nutrient-wise correlation matrices, regression analysis and principal component analysis analyses are suggested to determine the strength and direction of optical–nutrient relationship. The effects of cultivar, leaf age, illumination, disease and environmental factors are also taken into account. The framework created is a repeatable framework to assess the potential of digital colour and texture descriptors to be used as indirect measures of banana leaf nutritional status. This may help in the affordable screening of plant nutrients and precision agriculture using images after proper experimental validation.*

Keywords: Banana leaves; nutrient concentration; digital image analysis; colour features; texture analysis; Pearson correlation; GLCM; chemometrics; precision agriculture.

I. INTRODUCTION

Banana (Musa spp.) is a major horticultural crop grown throughout tropical and subtropical countries. Its economic and nutritional importance has promoted the development of crop management, soil fertility assessment, irrigation scheduling and plant monitoring of nutritional status. Essential mineral nutrients such as N, P, K, Mg and Fe play an important role in the productivity of banana plants, with a significant effect on the yield of the crop.

Mineral nutrients are involved in different physiological and biochemical aspects. Nitrogen is important for protein synthesis and chlorophyll production, phosphorus for energy flow and metabolic functions, potassium for osmotic regulation and enzyme activation, magnesium is central to chlorophyll molecule and iron is for various processes of electron transfer and chlorophyll production. A lack of, or imbalance in, these nutrients can cause physiological stress which can manifest as changes in the colour, texture, and appearance of leaf tissue.

The traditional nutrient diagnosis method is to observe the symptoms of plants, use soil test and chemical analysis of leaf tissues. While visual observation is quick and gives preliminary information, it is subject to

interpretation and difficulty in making sure that the information is not confused with other deficiency symptoms. Chemical analysis gives more direct quantitative evidence but is destructive, needs laboratory and trained staff.

The development of digital image processing has enabled the possibility of obtaining objective and numerical information from plant images. A digital image is a representation of the visible characteristics of an object in terms of the intensity of the pixels and the sequence of pixels in the image. Hence, colour models and texture descriptors can be used to quantify the variations in pigmentation and tissue appearance.

RGB model is the representation of red, green and blue intensities with HSV being the representation of hue, saturation and brightness. CIELAB gives perceptually organized colour coordinates, which is useful for investigating the difference in pigmentation of the leaves. Texture analysis, such as using grey-level co-occurrence matrices, can be used to quantify spatial variation associated with interveinal chlorosis, marginal discoloration and irregular tissue patterns.

These image-derived features can be associated with physiological conditions of the plants, but statistical analysis and chemical measurements must be used to determine the relationship between them and the concentrations of specific nutrients. The presence of a symptom is not a good indicator of nutrient deficiency, disease, ageing, or environmental injury.

In the present paper, therefore, the correlation between banana leaf colour and texture characteristics and the nutrient concentrations determined chemically is focused. It suggests an integrated methodological strategy that integrates image processing, analytical chemistry and statistical modelling to facilitate the development of scientifically validated nutrient-assessment systems.

II. RESEARCH PROBLEM

Although there are newer imaging methods available, it is still difficult to determine plant nutrient concentrations from visual leaf traits.

Often, leaf colour changes are due to several nutrients and other factors. However, it can be caused by several factors such as nitrogen deficiency, magnesium deficiency, iron deficiency, natural senescence, and environmental stress. Likewise, texture variations can be linked to nutrient deficiencies, infections, tissue damage, or acquisition parameters of the image.

In addition, the illumination, camera properties, leaf angle, and the image preprocessing affect the colour and texture descriptors.

It is thus necessary to develop a standard analytical tool for direct correlation between the optical features extracted from digital images of banana leaves and chemical measurements of their nutrient content, in order to study the statistical relationships between them.

III. OBJECTIVES OF THE STUDY

1. To obtain quantitative colour features from banana leaf images in RGB colour space, HSV colour space and CIELAB colour space.
2. To represent the texture of leaf surface by using statistical descriptors derived from GLCM.
3. To analyze the concentrations of nitrogen, phosphorus, potassium, magnesium and iron with suitable chemical methods.
4. To explore correlation between image-derived features and nutrient concentrations, using both Pearson and Spearman tests.
5. To establish colour and texture descriptors to supplement nutrients associated variation in leaves.
6. To assess the potential of the use of multivariate image features for non-destructive nutritional assessment.

IV. RESEARCH HYPOTHESES

H_{01}: Banana leaf colour features and chemically measured nutrient concentrations are not statistically different.

H_{12}: There is a statistically significant relationship between at least one banana leaf colour feature and chemical measurement of nutrient concentration.H11: At least one of the colour features of leaves of bananas has a statistically significant correlation with the nutrient concentration measured by chemical means.

H_{02}: No statistically significant correlation is found between the banana leaf texture features and the nutrient concentrations determined chemically.

H_{12}: There is at least one banana leaf texture feature that is statistically significantly correlated with the chemically determined nutrient concentration.

H_{03}: Texture descriptors do not contribute to the prediction of nutrients out of sample, compared to colour descriptors alone.

H_{13}: Including texture descriptors is beneficial for out-of-sample nutrient prediction over colour descriptors.

V. REVIEW OF LITERATURE

Digital imaging is playing a more prominent role in the fields of plant phenotyping, nutrient estimation and agricultural decisions. Optical measurements have been proven to give valuable indirect data on the leaf pigmentation and plant physiological status.

Richardson et al. (2002)[1] tested non-invasive techniques for measuring foliar chlorophyll concentration. Their work paved the way for the use of optical properties as a means of characterizing biochemical properties of leaves.

The relation between leaf chlorophyll concentration and spectral reflectance has been the focus of some investigations **(Gitelson et al., 2003),**[2] which gave the basis for understanding the optical responses to the variation of pigments.

Pagola et al. (2009) [3]have developed a digital colour-image method to evaluate the N nutrition of barley. Authors employed principal component analysis to form a greenness index and then compared the performance of this index to the SPAD chlorophyll readings.

Rorie et al. (2011)[4] investigated digital photographs for estimating the N concentration of maize leaves. They found good correlations between the calibrated dark-green colour index and the actual leaf nitrogen concentration, showing the potential for cheap imaging systems under controlled experimental conditions.

Li et al. (2014)[5] summarized the imaging technologies used for plant phenotyping and the role of digital imaging in quantitative analysis of plant structure and physiological characteristics.

Singh et al. (2016)[6] looked at machine learning approaches to high-throughput plant stress phenotyping, particularly regarding combining image features and computational modeling.

---

[1] Richardson, A. D., Duigan, S. P., & Berlyn, G. P. (2002). An evaluation of noninvasive methods to estimate foliar chlorophyll content. New Phytologist, 153(1), 185–194. https://doi.org/10.1046/j.0028-646X.2001.00289.x

[2] Gitelson, A. A., Gritz, Y., & Merzlyak, M. N. (2003). Relationships between leaf chlorophyll content and spectral reflectance and algorithms for non-destructive chlorophyll assessment in higher plant leaves. Journal of Plant Physiology, 160(3), 271–282. https://doi.org/10.1078/0176-1617-00887

[3] Pagola, M., Ortiz, R., Irigoyen, I., Bustince, H., Barrenechea, E., Aparicio-Tejo, P., Lamsfus, C., & Lasa, B. (2009). New method to assess barley nitrogen nutrition status based on image colour analysis: Comparison with SPAD-502. Computers and Electronics in Agriculture, 65(2), 213–218. https://doi.org/10.1016/j.compag.2008.10.003

[4] Rorie, R. L., Purcell, L. C., Karcher, D. E., & King, C. A. (2011). The assessment of leaf nitrogen in corn from digital images. Crop Science, 51(5), 2174–2180. https://doi.org/10.2135/cropsci2010.12.0699

[5] Li, L., Zhang, Q., & Huang, D. (2014). A review of imaging techniques for plant phenotyping. Sensors, 14(11), 20078–20111. https://doi.org/10.3390/s141120078

[6] Singh, A., Ganapathysubramanian, B., Singh, A. K., & Sarkar, S. (2016). Machine learning for high-throughput stress phenotyping in plants. Trends in Plant Science, 21(2), 110–124. https://doi.org/10.1016/j.tplants.2015.10.015

Plant disease detection by imaging sensors was reviewed by **Mahlein (2016)**[7] and the importance of optical measurements for assessing physiologic and stress-related plant properties was emphasized.

Barbedo (2019)[8] has reviewed the technologies of proximal imaging and machine learning used for detection of plant nutrient deficiency. The study presented RGB, multispectral, hyperspectral and fluorescence imaging, and focused on challenges regarding nutrient specific diagnosis.

Sunitha et al. (2023)[9] released the labelled dataset of banana leaf image that encompasses the various nutritional deficiency categories. This will be useful for developing and evaluating image-analysis methods for bananas, but will require chemical nutrient measurement for correlation studies that involve concentrations.

5.1 Research Gap

While some earlier studies have showed the feasibility of plant assessment from images, there are few studies that have quantified the relation between the combined banana leaf colour–texture descriptors and the concentrations of several nutrients obtained from chemical assays.

The present research framework seeks to fill this gap by introducing paired image and chemical measurements, correlation analysis, correcting for confounding variables, and independent validation done on a nutrient basis.[10]

VI. MATERIALS AND METHODS

6.1 Experimental Design

The proposed investigation is a quantitative analytical design that involves using digital image acquisition, optical feature extraction, chemical nutrient determination, and statistical analysis.

The basic observation is a pair of data, one a chemical measurement, one a feature derived from an image of the banana leaf.

In order to prevent pseudoreplication, several images of a single leaf should be considered as repeated technical replications and not independent biological replicates.

6.2 Leaf Sampling

Banana leaves should be picked from plants grown under various nutritional conditions. The cultivar, developmental stage, leaf position, visible symptoms, irrigation conditions and management history should be noted.

Leaf position should be the same for all samples taken and should be the diagnostic leaf position of the cultivar and crop stage. Severely diseased leaves, insect damaged leaves, leaves with mechanical injury should be either excluded according to pre-defined criteria or analysed separately.[11]

6.3 Digital Image Acquisition

Photographs should be taken with a digital camera and standardized lighting conditions, high resolution.

It is recommended that a colour-reference chart is included to assist in correcting differences in cameras and lighting.

---

[7] Mahlein, A.-K. (2016). Plant disease detection by imaging sensors—Parallels and specific demands for precision agriculture and plant phenotyping. Plant Disease, 100(2), 241–251. https://doi.org/10.1094/PDIS-03-15-0340-FE

[8] Barbedo, J. G. A. (2019). Detection of nutrition deficiencies in plants using proximal images and machine learning: A review. Computers and Electronics in Agriculture, 162, 482–492. https://doi.org/10.1016/j.compag.2019.04.035

[9] Sunitha, P., Uma, B., Channakeshava, S., & Suresh Babu, C. S. (2023). A fully labelled image dataset of banana leaves deficient in nutrients. Data in Brief, 48, 109155. https://doi.org/10.1016/j.dib.2023.109155

[10] Barbedo, J. G. A. (2013). Digital image processing techniques for detecting, quantifying and classifying plant diseases. SpringerPlus, 2, 660. https://doi.org/10.1186/2193-1801-2-660

[11] Barbedo, J. G. A. (2016). A review on the main challenges in automatic plant disease identification based on visible range images. Biosystems Engineering, 144, 52–60. https://doi.org/10.1016/j.biosystemseng.2016.01.017

Distance, exposure, ISO sensitivity, white balance, resolution and orientation of image should be considered when setting up image acquisition parameters.

6.4 Image Preprocessing

The image processing includes colour calibration, background elimination, segmentation of leaves, noise suppression and identification of valid leaf pixels.

A binary segmentation mask can be defined as:

$$M(x,y) = \begin{cases} 1, if\ (x,y) is\ a\ leaf\ pixel \\ 0, if (x,y) is\ a\ background\ pixel \end{cases}$$

Optical feature calculations should only be performed on segmented leaf-pixels.

6.5 Extraction of Colour Features

RGB analysis should include the calculation of the mean intensity of red, green and blue, the standard deviations of red, green and blue, and the normalised red, green and blue components.

The normalized green component is:

$$g = \frac{G}{R+G+B}$$

The HSV should contain the circular mean value of the hues, the mean value of the saturations, and the mean value of the brightness.

The values of L*, a*, and b* should be used as CIELAB descriptors. With proper colour calibration these can measure the lightness and green–yellow colour variation.[12]

6.6 Extraction of Texture Features

The conditions for performing GLCM analysis should be consistent in terms of image resolution, quantization, pixel distance and orientation.

The 4 main descriptors should be taken out:

Texture feature	Interpretation
Contrast	Local variation in grey-level intensity
Correlation	Spatial dependence between neighbouring pixel values
Energy	Uniformity of grey-level co-occurrence patterns
Homogeneity	Concentration of co-occurrences near the matrix diagonal

Texture could be relevant for the description of interveinal chlorosis, marginal discoloration and patchy tissue appearance.

6.7 Chemical Determination of Nutrient Concentrations

Leaf samples taken should be dried, ground, and analysed by validated laboratory technique for corresponding analysis.

Table 1. Proposed chemical analytical methods

Nutrient	Analytical method	Reporting unit
Nitrogen	Kjeldahl digestion or combustion analysis	% dry mass
Phosphorus	Validated digestion and colorimetry	% dry mass
Potassium	Flame photometry or ICP-OES	% dry mass
Magnesium	AAS or ICP-OES	% dry mass
Iron	AAS or ICP-OES	mg/kg dry mass

The laboratory quality control programme should contain method blank, calibration standard, reference materials and replicate analyses.[13]

[12] Barbedo, J. G. A. (2018). Factors influencing the use of deep learning for plant disease recognition. Biosystems Engineering, 172, 84–91. https://doi.org/10.1016/j.biosystemseng.2018.05.013

IJETIR
ISSN (Online) 2583-0554
International Journal of Emerging Technologies and Innovative Research (IJETIR)
Volume 5, Issue 7, July 2025
Impact Factor: 5.731

6.8 Correlation Analysis

If the requirements of Pearson correlation are met, then it can be used to assess approximately linear relationships between continuous image features and nutrient concentrations.

$$r = \Sigma_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y}) \; / \; \sqrt{\{[\Sigma_{i=1}^{n}(x_i - \bar{x})^2][\Sigma_{i=1}^{n}(y_i - \bar{y})^2]\}}$$

Spearman rank correlation should be employed additionally when the relationship is monotonic, but not necessarily linear, and when there are outliers and distributional properties that warrant the use of rank correlation.

Correlation coefficients have the range of −1 to +1. Positive values for two variables mean that the values of the variables tend to go up together, and negative values mean that the values of the variables tend to go down together.

Sample size, correlation coefficient, confidence interval and p-value should be reported. When performing tests of numerous optical–nutrient combinations, the false-discovery-rate adjustment should be used.

6.9 Multivariate Analysis

Standardized image features should be analyzed by PCA to explore redundancy and key image variation patterns.

Partial least squares regression or ridge regression can be used to assess the ability of combined colour and texture features to predict nutrient concentrations.

R2, RMSE and MAE should be used as the metrics for assessing predictive performance on held-out biological samples.[14]

VII. RESULTS AND DISCUSSION

This section discusses the reporting framework and scientifically based interpretation of the expected optical–nutrient relationships. The experimental data are not provided, and thus the significance values and numerical correlation coefficients are not shown as observed values.

7.1 Colour Characteristics and Nutrient Concentrations

Leaf pigmentation may be related to the availability of nitrogen and magnesium which are involved in photosynthetic processes. This makes colour descriptors of greenness and chlorosis good candidates for correlation analysis.

Chlorosis, particularly on younger leaves may also result from iron deficiency, while symptoms caused by potassium deficiencies can include marginal discoloration and necrosis.

Optical relationships can vary depending on environmental stress, cultivar, severity of deficiency and leaf maturity.

Table 2. The nutrient-wise correlation analysis is proposed.

Nutrient	Image feature	Proposed relationship to examine
Nitrogen	Normalized green intensity	Association with pigmentation
Nitrogen	CIELAB a*	Association with green chromaticity
Phosphorus	Hue and saturation	Possible pigmentation variation
Potassium	Marginal colour fraction	Association with marginal symptoms
Magnesium	Regional b*	Association with interveinal yellowing
Iron	a*, b* and yellow-area fraction	Association with chlorosis

The direction and magnitude of each relationship must be determined empirically.

The direction and the strength of each relationship needs to be established by experiment.

[13] Camargo, A., & Smith, J. S. (2009). Image pattern classification for the identification of disease causing agents in plants. Computers and Electronics in Agriculture, 66(2), 121–125. https://doi.org/10.1016/j.compag.2009.01.003

[14] Haralick, R. M., Shanmugam, K., & Dinstein, I. (1973). Textural features for image classification. IEEE Transactions on Systems, Man, and Cybernetics, SMC-3(6), 610–621. https://doi.org/10.1109/TSMC.1973.4309314

IJETIR
ISSN (Online) 2583-0554
International Journal of Emerging Technologies and Innovative Research (IJETIR)
Volume 5, Issue 7, July 2025
Impact Factor: 5.731

7.2 Texture features and nutrient concentrations

Texture descriptors can be used to describe spatial patterns which can be different from the mean colour measurements.

For instance, interveinal chlorosis might produce a greater spatial heterogeneity, whereas relatively uniform chlorosis might have greater impact on average colour than on texture.

Therefore, examining the GLCM contrast, correlation, energy, and homogeneity should be done along with the colour features, but it should not be considered as some nutrient-specific indicators.[15]

7.3 Correlation Matrix

The main quantitative outcome of the experimental study should be a full correlation matrix.

Table 3. This is a correlation matrix reporting template.

Image feature	N	P	K	Mg	Fe
Mean green intensity	r, p	r, p	r, p	r, p	r, p
Mean hue	r, p	r, p	r, p	r, p	r, p
CIELAB a*	r, p	r, p	r, p	r, p	r, p
CIELAB b*	r, p	r, p	r, p	r, p	r, p
GLCM contrast	r, p	r, p	r, p	r, p	r, p
GLCM homogeneity	r, p	r, p	r, p	r, p	r, p

After analysis of paired measurements each cell should be filled with the calculated correlation coefficient and the significance value.

7.4 Interpretation of Potential Associations

If there is a statistically significant correlation between greenness and concentration of nitrogen, this would support the physiological role of nitrogen in chlorophyll related processes. However, this would not prove a causal relationship or specific to nitrogen.

Likewise, if texture contrast and magnesium concentration were found to be related, this could be interpreted as a relationship with spatial chlorosis; however, the association would need to be confirmed as not being caused by disease, ageing or any other nutrient conditions.

Within one experimental environment, strong correlations were also not necessarily applicable to other cultivars or field environments. Therefore, it is important that external validity is tested.[16]

7.5 Colour-Only vs Combined Feature Models

The usefulness of the texture analysis should be evaluated using two models: colour model, and colour and texture model.

Table 4. Comparative model evaluation proposed.

Model	Input features	Evaluation criteria
Model A	RGB, HSV and CIELAB	Test R^2, RMSE, MAE
Model B	GLCM texture	Test R^2, RMSE, MAE
Model C	Colour + GLCM texture	Test R^2, RMSE, MAE

An enhancement to Model C, relative to Model A, would be desirable if it is significant in independent test samples.[17]

[15] Singh, V., & Misra, A. K. (2017). Detection of plant leaf diseases using image segmentation and soft computing techniques. Information Processing in Agriculture, 4(1), 41–49. https://doi.org/10.1016/j.inpa.2016.10.005

[16] Usha, K., & Singh, B. (2013). Potential applications of remote sensing in horticulture—A review. Scientia Horticulturae, 153, 71–83. https://doi.org/10.1016/j.scienta.2013.01.008

[17] Villaseñor-Ortiz, D., Prado, R. de M., Silva, G. P. da, & Lata-Tenesaca, L. F. (2022). Applicability of DRIS in bananas based on the accuracy of nutritional diagnoses for nitrogen and potassium. Scientific Reports, 12, 18125. https://doi.org/10.1038/s41598-022-22554-w

VIII. PRACTICAL APPLICATIONS

Proposed approach has potential applications in banana nutrient monitoring, agricultural extension and precision crop management.

With a calibrated digital photograph one could have an objective record of the leaf pigmentation and also be able to identify the plants that need further study. Multiple image measurements can be used to monitor changes visible throughout the crop growth stages.

In addition, with a soundly designed screening strategy, image-based assessment may decrease the need for unnecessary laboratory testing. Nutrient specific recommendations for fertilizer use, however, should continue to be made based on proper chemical analysis and agronomic interpretation.

IX. LIMITATIONS AND FUTURE SCOPE

The main constraint of visible image analysis is that the nutrient concentration is not measured directly from the RGB colour or texture information. Optical features are indirect physiological and visual responses which can be affected by a number of factors.

Further studies are required with controlled nutrient treatments, more cultivars of bananas, various different stages of development, field light conditions, and separate chemical testing.

Longitudinal observations may be useful to differentiate temporary colour changes from permanent nutritional disorders. Additional spectral information can also be used to estimate nutrients compared to the conventional digital images of the photos, which can also be used in multispectral and hyperspectral imaging.[18]

X. CONCLUSION

The correlations between banana leaf colour and texture features were performed with the nutrient concentrations determined by chemical analysis, which is a promising research area for precision agriculture. Quantitative measures of leaf pigmentation were provided by RGB, HSV, and CIELAB descriptors, and complementary information of spatial heterogeneity was provided by the GLCM texture features. Combination of these image-derived variables and laboratory measurements of nitrogen, phosphorus, potassium, magnesium and iron provide a basis for studying image–nutrient relationships.

The suggested approach is based on standardisation of imaging, chemical reference measurements, correlation analysis, and statistical stand-alone validation. While the literature indicates that there is potential for image-based plant nutrient assessment, reliable conclusions with respect to specific nutrients can only be reached based on experimentally measured paired datasets.

This method, if proven valid, could be used in nutritional screening in a cost-effective and non-destructive way, and be used in the management of banana crops.

REFERENCES

1. Barbedo, J. G. A. (2013). Digital image processing techniques for detecting, quantifying and classifying plant diseases. SpringerPlus, 2, 660. https://doi.org/10.1186/2193-1801-2-660
2. Barbedo, J. G. A. (2016). A review on the main challenges in automatic plant disease identification based on visible range images. Biosystems Engineering, 144, 52–60. https://doi.org/10.1016/j.biosystemseng.2016.01.017
3. Barbedo, J. G. A. (2018). Factors influencing the use of deep learning for plant disease recognition. Biosystems Engineering, 172, 84–91. https://doi.org/10.1016/j.biosystemseng.2018.05.013

[18] Wold, S., Sjöström, M., & Eriksson, L. (2001). PLS-regression: A basic tool of chemometrics. Chemometrics and Intelligent Laboratory Systems, 58(2), 109–130. https://doi.org/10.1016/S0169-7439(01)00155-1

4. Barbedo, J. G. A. (2019). Detection of nutrition deficiencies in plants using proximal images and machine learning: A review. Computers and Electronics in Agriculture, 162, 482–492. https://doi.org/10.1016/j.compag.2019.04.035
5. Camargo, A., & Smith, J. S. (2009). Image pattern classification for the identification of disease causing agents in plants. Computers and Electronics in Agriculture, 66(2), 121–125. https://doi.org/10.1016/j.compag.2009.01.003
6. Gitelson, A. A., Gritz, Y., & Merzlyak, M. N. (2003). Relationships between leaf chlorophyll content and spectral reflectance and algorithms for non-destructive chlorophyll assessment in higher plant leaves. Journal of Plant Physiology, 160(3), 271–282. https://doi.org/10.1078/0176-1617-00887
7. Haralick, R. M., Shanmugam, K., & Dinstein, I. (1973). Textural features for image classification. IEEE Transactions on Systems, Man, and Cybernetics, SMC-3(6), 610–621. https://doi.org/10.1109/TSMC.1973.4309314
8. Li, L., Zhang, Q., & Huang, D. (2014). A review of imaging techniques for plant phenotyping. Sensors, 14(11), 20078–20111. https://doi.org/10.3390/s141120078
9. Mahlein, A.-K. (2016). Plant disease detection by imaging sensors—Parallels and specific demands for precision agriculture and plant phenotyping. Plant Disease, 100(2), 241–251. https://doi.org/10.1094/PDIS-03-15-0340-FE
10. Pagola, M., Ortiz, R., Irigoyen, I., Bustince, H., Barrenechea, E., Aparicio-Tejo, P., Lamsfus, C., & Lasa, B. (2009). New method to assess barley nitrogen nutrition status based on image colour analysis: Comparison with SPAD-502. Computers and Electronics in Agriculture, 65(2), 213–218. https://doi.org/10.1016/j.compag.2008.10.003
11. Richardson, A. D., Duigan, S. P., & Berlyn, G. P. (2002). An evaluation of noninvasive methods to estimate foliar chlorophyll content. New Phytologist, 153(1), 185–194. https://doi.org/10.1046/j.0028-646X.2001.00289.x
12. Rorie, R. L., Purcell, L. C., Karcher, D. E., & King, C. A. (2011). The assessment of leaf nitrogen in corn from digital images. Crop Science, 51(5), 2174–2180. https://doi.org/10.2135/cropsci2010.12.0699
13. Singh, A., Ganapathysubramanian, B., Singh, A. K., & Sarkar, S. (2016). Machine learning for high-throughput stress phenotyping in plants. Trends in Plant Science, 21(2), 110–124. https://doi.org/10.1016/j.tplants.2015.10.015
14. Singh, V., & Misra, A. K. (2017). Detection of plant leaf diseases using image segmentation and soft computing techniques. Information Processing in Agriculture, 4(1), 41–49. https://doi.org/10.1016/j.inpa.2016.10.005
15. Sunitha, P., Uma, B., Channakeshava, S., & Suresh Babu, C. S. (2023). A fully labelled image dataset of banana leaves deficient in nutrients. Data in Brief, 48, 109155. https://doi.org/10.1016/j.dib.2023.109155
16. Usha, K., & Singh, B. (2013). Potential applications of remote sensing in horticulture—A review. Scientia Horticulturae, 153, 71–83. https://doi.org/10.1016/j.scienta.2013.01.008
17. Villaseñor-Ortiz, D., Prado, R. de M., Silva, G. P. da, & Lata-Tenesaca, L. F. (2022). Applicability of DRIS in bananas based on the accuracy of nutritional diagnoses for nitrogen and potassium. Scientific Reports, 12, 18125. https://doi.org/10.1038/s41598-022-22554-w
18. Wold, S., Sjöström, M., & Eriksson, L. (2001). PLS-regression: A basic tool of chemometrics. Chemometrics and Intelligent Laboratory Systems, 58(2), 109–130. https://doi.org/10.1016/S0169-7439(01)00155-1