An Image Processing-Based Statistical Method for Estimating Nutrient Deficiencies in Grape Plants During the Growing Season

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Agriculture plays a very important role in the provision of food surplus to expanding population, contribution to capital formation, providing raw material to industries, market for industrial products and major contribution in international trade. To enhance the quality and quantity of the agriculture product there is a need to adopt the new technology. Image processing approach is non-invasive technique which provides consistent, reasonably accurate, less time consuming and cost-effective solution for farmers to manage fertilizers and pesticides. The objective of this study is to analyze the nutrition of grape plant using Wavelength algorithmand statistical method regression analysis is used in our work for the nutrient estimation. The relative requirements of nitrogen, phosphorus and potassium in grapes vary with the growth stages of grapes. There is a high-level requirement of N during the vegetative growth stage, P requirement is high during flowering stage and K requirement is more in crop maturity stage. So pruning was carried out in two stages i.e., in April and in October. This study is carried out in grape farms of Theni District of Tamil Nadu for estimating the macro nutrition nitrogen (N), phosphorus (P) and potassium (K) to analyze the yield. The results showed that the overall identification accuracies of NPK deficiencies were 86.15, 87.69, 90.00 and 89.23% for the two pruning stages.

Povzetek: Razvili so neinvazivno metodo za oceno pomanjkanja hranil v grozdju s pomočjo analize slik in statističnih metod, kar omogoča prepoznavanje pomanjkanja dušika, fosforja in kalija ter s tem izboljšanje kakovosti in količine pridelka.

1 Introduction

The agriculture sector is the main contributor in the Indian economy and is doing well in white, green and blue revolution. According to APEDA, by 2014 exports of Indian agriculture will reach 5% of total production of the world and rank 10th in the ranking [1]. Precision agriculture is a new and developing technology which leads to incorporating the advanced techniques to enhance farm output and also enrich the farm inputs in a profitable and environmentally sensible manner. Farm inputs were important parameters to be controlled and if not will result in adverse effects causing reduction in yield, deteriorating plant health, etc. Irrigation/Water stress, Fertilizers, pesticides and quality of yield were the major factors of concern in agriculture. Most of the time expertise is required to analyze the problems, which may be a time consuming and costly issue in developing countries. Image processing is one of the tools which can be applied to measure the parameters related to agronomy with accuracy and economy. Applications of image processing in agriculture can be broadly classified in two categories: first one depends upon the imaging techniques and the second one based on applications.

Less yield, higher cost of production due to labour scarcity and fertilizer cost are the major challenges before the farmers. To enhance the quality and quantity of the agriculture product there is a need to adopt the new technology. Fertilizer and pesticide management requires early and cost-effective solutions which will lead to higher yield. Image processing approach is a non-invasive technique which provides consistent, reasonably accurate, less time consuming and cost-effective solutions for farmers to manage fertilizers and pesticides. The soft computing techniques are helpful in developing the knowledge-based systems, and may be effectively utilized to develop the expert system. This system will be helpful for farmers to find the solutions to their farming problems in the existing system such as Adaptation to climate change in viticulture, integration with other nutrient assessments and expansion to other cros and environments. The research objective is aimed to identify/develop color models for Fertilizer's estimation viz. Nitrogen, Phosphorous, Potassium and Magnesium for grapes as a horticulture product.

2 Related works

Plants need a certain number of macronutrients (nitrogen, phosphorus, etc.) and micronutrients (Zinc, Boron, etc.) to grow and stay healthy. These Nutrients alter and regulate the functioning of plants and produce qualitative and quantitative changes in plant yield. Nutrient deficiency may result in weaker plants. Nutrient deficiencies make plants more susceptible to diseases. Fertilizers are the supplements for the plants to grow healthier. In case of grapevines, the deficiencies or overdoses are observed by visual inspections by experts. Availability of experts on time and their consultancy cost are the major issues. Nitrogen application to grapevine in excess form results in excessive growth of shoots at the cost of fruit set. This will also result in a delay in maturity and poor bud formation in the following season [1].

The Proper application of fertilizers and pesticides can save cost of production. In most of the cases, deficiencies are observed by a change in the color of leaves in which Chlorophyll is an important ingredient. Chlorophyll is a molecule in a leaf which is responsible for photosynthesis action. The carbohydrates produced in photosynthesis are used as food for growth of plants and fruit. Various methods are proposed to analyze the nutrients based on chemical analysis such as leaf analysis, petiole analysis [2]

Vasifa A. Aglave et al., reported a survey for chlorophyll content, disease severity and leaf area measurement. Leaf area measurement techniques viz. grid counting, paper weighing, leaf area meter, digital image analysis using different techniques were reported. Naked eye observation, image processing techniques like chain code, bounding box, segmentation were reported for measuring disease severity along with different chlorophyll content measurement [3]. M.M. Ali et al., presented different non destructive handheld meter techniques such as leaf color chart, SPAD meter, N-tester, Image analysis to estimate foliar N status of plant. Comparison of these methods was also highlighted on the basis of applicability, accuracy, the effect of environment, etc. [4].

The color image analysis became a popular and cost-effective method for chlorophyll and nutrient estimation. Paula F. Murakami has developed digital imaging software like scion which was used for analysis and quantification of chlorophyll using leaf color. The software calculates the percentage green and red for chlorophyll estimation. RGB and HSV color models were considered in development [5]. Parviz Moghaddam et al., developed an algorithm to estimate chlorophyll using a video camera in which it was shown that the red and blue elements were highly correlated with it. Normalized difference of red and blue was effectively used to estimate chlorophyll under different meteorological conditions. The multilayer perceptron neural network was developed using R, G and B values for chlorophyll estimation. The results show the high coefficient of determination (R2) and low mean square error where the estimated values were compared with chlorophyll SPAD meter [6].

Mario Cupertino da Silva et al., presented the work that showed the correlation between vegetation indices and nitrogen. The Correlation between vegetation indices and nitrogen leaf content and dry matter at different stages for fertilization was calculated with IR camera and digital camera. The study revealed that the high positive correlation decreases as the number of days increases after fertilization and green spectral band is more useful for nitrogen discrimination. Three indices NDVI, GNDVI and SAVI were evaluated and observed that GNDVI was the best [7].

Han Yuzhuet al., proposed a method of nitrogen estimation for pepper in flowering and fruiting using color image processing. Different functions of RGB were considered and correlated with nitrogen. Regression analysis for inorganic nitrogen in soil, total nitrogen, nitrogen concentration and SPAD meter readings were done and all show negative coefficient for the considered function. N applications were given in different treatments [8].

Gloria F. Mata-Donjuan et al., induced five levels of nitrogen deficiencies and proposed improved hue, luminance and saturation color space which is less susceptible to illumination variation. IHLS was used to estimate the nitrogen for tomato seedlings. Image processing methodologies like segmentation, RGB to IHLS conversion and image analysis were implemented. He showed better statistical relation with nitrogen values obtained from chemical analysis. Estimation N was based on components histograms in IHLS and in the fusion of saturation and hue [9].

Table 1 summarizes the literature survey of research methodology, Key focus, research findings, challenges and future research directions.

Table 1: Summary of literature survey and its contributions

Ref.	Topic	Key Focus	Methodology/ Technology	Application /Outcome	Limitations /Challenges	Future Research Directions	Key Findings
[1]	Vitinotes	Viticulture research	Review of viticulture practices	Enhancing viticulture through research insights	General applicability across regions	Adaptation to climate change in viticulture	Insights into improving viticulture through research

[2]	Grapevine structure and function	Grapevine biology	Analysis of grapevine anatomy and physiology	Better viticulture practices	Limited to structural aspects	Integration with genetic research	Detailed understanding of grapevine anatomy supports better practices
[3]	Imaging techniques	Leaf area, disease severity, chlorophyll content	Imaging technology and algorithms	Non-destructive plant health analysis	Accuracy of imaging algorithms	Development of more robust algorithms	Imaging techniques can accurately assess plant health
[4]	Leaf nitrogen determination	Nitrogen content in leaves	Handheld meters	Efficient nitrogen assessment	Limited to nitrogen; excludes other nutrients	Integration with other nutrient assessments	Handheld meters provide reliable nitrogen measurements
[5]	Leaf color analysis	Digital leaf color analysis	Digital imaging software	Standardized leaf color measurement	Software complexity and accuracy	Simplification and automation of software	Digital imaging offers standardized leaf color analysis
[6]	Chlorophyll content estimation	Chlorophyll in sugar beet leaves	Machine vision	Precise chlorophyll content estimation	Limited to sugar beet; may not apply to other crops	Expansion to other crops and environments	Machine vision accurately estimates chlorophyll content
[7]	Vegetation indices correlation	Vegetation indices, nitrogen, dry matter production	Image analysis	Improved vegetation health assessment	Correlation may vary by species and region	Exploration of species-specific indices	Yes
[8]	Nitrogen determination in pepper plants	Nitrogen content estimation using RGB	RGB color image analysis	Effective nitrogen assessment for pepper plants	RGB analysis might be affected by lighting conditions	Improved robustness against environmental variations	RGB analysis is effective but sensitive to light conditions
[9]	Nitrogen estimation in tomato seedlings	Nitrogen estimation using IHLS color space	IHLS color space	Accurate nitrogen estimation in tomato seedlings	IHLS method complexity	Application to other nutrient estimations	IHLS color space offers precise nitrogen estimation
[10]	Grapevine nutritional status	Grapevine nutrition estimation	Proximal sensing techniques	Non-destructive monitoring of grapevine health	Limited to proximal sensing; excludes remote sensing	Combination with remote sensing technologies	Proximal sensing is effective for real-time nutritional assessment
[11]	Grapevine nutrition	Remote sensing-based estimation	Remote sensing	Accurate field-based grapevine nutrition monitoring	Sensitivity to environmental factors	Refinement of remote sensing techniques	Remote sensing accurately estimates grapevine nutrition
[12]	Nutrient estimation in grapevine leaves	Nitrogen, phosphorus, potassium, magnesium content estimation	Near-infrared spectroscopy (NIRS)	Rapid nutrient estimation in grapevines	NIRS may require calibration for different environments	Development of universal calibration models	NIRS provides quick and accurate nutrient estimation

[13]	Vineyard nutritional status	Vineyard nutrition assessment	Proximal sensing	Challenges and opportunities in vineyard management	Limited to proximal sensing; excludes other methods	Integration with comprehensive vineyard management systems	Proximal sensing reveals key challenges in vineyard management
[14]	Deficit irrigation	Water-saving in horticulture	Integrative plant biology	Water conservation and improved horticultural practices	May not apply to all horticultural crops	Testing in diverse horticultural environments	Deficit irrigation effectively conserves water without harming crops

3 Materials and methods

3.1 Experimental design

The goal of the experiment was to investigate the grape plant's yield analysis under various levels of NPK nutrition. The experiment was carried out in commercial vineyards in areas around Theni of Tamil Nadu. The vines were planted in a vertical shoot-positioning technique with a north-south row orientation at a distance of 2 m. There were five different grapevine varieties utilised in this experiment. Hydroponics with a nutrient solution formula was applied to cultivate the grape plants. After berry set, the six first basal leaves of the selected plants were carefully plucked.

3.2 Sample/ leaf selection

Changes in nutrients are reflected in plant appearance or chemical composition of plant tissues or petioles. Plant analysis for nutrient contents can be carried out either by chemical analysis or visual diagnosis of deficiencies/ toxicity. Standards are developed for petiole sampling through research in various parts of the world and India (NRC or MRDBS, Pune). These standards are for optimal growth of grapevine. Since the nutritional requirement varies over the season, it is necessary to match the standard requirement of nutrients [3]. While sampling, few factors need to be considered viz. time, site, and plant part of sample.

3.3 Image acquisition

Images are acquired with proper selection of camera and background. In two different seasons—one in May or June and the other in November or December—pictures are taken outside in the sunshine. Days with plenty of sunshine were selected to reduce shadow variations and increase light uniformity. The camera's flash was disabled in order to prevent glare and reflections, which could skew colour and intensity measurements that are essential for precise analysis. Leaf images are captured with a digital camera having a CCD sensor of Nikon Coolpix S570. The model is selected considering the general availability and cost effectiveness. CCD camera is preferred than CMOS as CCD's are less susceptible to noise, to maintain image quality under varying light conditions as compared to CMOS. The camera is kept at a distance of 7-8 inches from the ground level or leaf blade surface to ensure consistency in capturing image details across all samples. At a resolution of 3 mega pixels (2048*1536), the camera was configured in Normal mode. Fine details in leaf texture and colour can be captured at this resolution, which strikes a balance between image quality and file size. In order to keep things simple and make the leaf the main focal point, a neutral background was selected. Segmentation during image processing is aided and colour interference is less likely.

The following image pre-processing steps are needed to ensure high quality image acquisition:

Color calibration: Images are colour calibrated prior to processing in order to correct for lighting-related colour variations. Accurate colour representation is aided by this, and extracting RGB, HSV, and other indices depends on it.

Noise reduction: To improve the accuracy of color-based indices such as Opponent HSV and modified indices, further filtering is carried out to eliminate any remaining noise, even though CCD sensors naturally minimise noise.

Thresholding: The three thresholds (80, 100, and 112) on pixel values are set during pre-processing. This is necessary in order to separate particular colour bands and characteristics associated with estimating nutrients.

Segmentation: To make sure that just the leaf pixels are examined, the leaf region is divided from the background. To extract colour parameters independently of surrounding elements, this segmentation is essential.

3.4 Nutrient analysis for post april pruning

Sampling techniques after April pruning and October pruning are different. The annual cycle growth of grapes involves many processes and events. The timing and duration of development of events vary due to rootstock variety, local climate and seasonal weather [4]. In India because of temporal zone the growth of the plant continues, hence the pruning process was developed for two times. We can classify the development processes into stages after April pruning viz. vegetative growth/ bud differentiation stage and after October pruning viz. flower cluster initiation (Bloom), fruit maturity and harvest. Many of these processes overlap each other during the development process. Vigorous and healthy growth is required during the pre - initiation stage of floral primordial, slow and less growth in fruit bud differentiation is required for higher yield of grapes. The need for N is higher during plant growth, the need for P is higher during flowering and the need for K is higher during crop maturity.

3.5 Nitrogen estimation using wavelength algorithm

The human color perception is scientifically and technically defined by colorimetry. Human visual sensitivity, illumination sources and spectral measurements are the major issues in colorimetry. The tri stimulus values X, Y and Z have been defined by CIE which represents the human color vision mathematically. CIE has defined various illumination sources such as A, B, C and D, but for this experiment we considered daylight D65 source with 1964 color observer. The method of CIE colorimetric specification depends on rules of color matching by additive color mixture. Mathematically, CIEXYZ is represented as equations 1 to 3 where $S(\lambda)$is object spectrum, $E(\lambda)$is the spectral power distribution (SPD) of an illuminant, and the color matching functions (CMFs) $A(\lambda) = \{ x(\lambda), y(\lambda), z(\lambda)\}$ where λ is the wavelength.

$$X = \int \bar{x}(\lambda)E(\lambda)S(\lambda)\, d\lambda \quad \text{---------- Eqn 1}$$

$$Y = \int \bar{y}(\lambda)E(\lambda)S(\lambda)\, d\lambda \quad \text{---------- Eqn 2}$$

$$Z = \int \bar{z}(\lambda)E(\lambda)S(\lambda)\, d\lambda \quad \text{---------- Eqn 3}$$

Often tri stimulus space is represented in 2D space and can be represented by normalized component as equation 4 to 6

$$x = \frac{x}{(x+y+z)} \quad \text{---------- Eqn 4}$$

$$y = \frac{y}{(x+y+z)} \quad \text{---------- Eqn 5}$$

$$z = \frac{z}{(x+y+z)} \quad \text{---------- Eqn 6}$$

Most of the researchers used the chlorophyll meter to estimate or relate the nutrient parameters of the plants. Chlorophyll measurement is a non-destructive method which has been proved to be less costly and effective method. Chlorophyll meter works on the principle of emission of two frequencies of light, one is red at wavelength 660 nm and other is infrared at 940 nm. Leaf chlorophyll absorbs red light but infrared is not absorbed. The difference between the absorptions is calculated as an index of chlorophyll. Since nitrogen is related with the chlorophyll contents, concept of chlorophyll meter can be extended for measurement of nitrogen from images. In this experiment an effort has been made to estimate the wavelength from leaf image and is illustrated as in figure 1. Values of RGB are calculated using XYZ for respective wavelength of CIE1964 full record. These RGB values are useful in interpolation to estimate the wavelength based on image.

In this experiment an innovative effort has been made to estimate the wavelength of RGB image and used as new index to estimate nitrogen. To achieve the principle of wavelength-based estimation of nutrient parameter following algorithm is developed.

The calculated wavelength is the function of r, g and b values of the image and can be represented as equation 7

$$\lambda = f(r,g,b) \quad \text{---------- Eqn 7}$$

April pruning data along with variation is used for analysis purpose. Depending on the values of RGB and chart prepared, wavelength is interpolated for the corresponding image/plot. Using estimated wavelength index Lambda (L) regression analysis using LABfit

3.6 Nutrient analysis for post october pruning

The sample collection after October pruning differs from April pruning, also the nutrient requirement also differs at this stage. After October pruning the leaf which is opposite to the basal bunch collected as a sample. As discussed in a previous chapter the samples are collected from various fields in the Theni district with preferences to collect it from fields of April pruned samples. As time of pruning differs and inputs applied by farmers also vary, the samples collected after October pruning are also with uncontrolled input i.e. information of applied fertilizers is unknown or not considered.

N requirement is high after April pruning to promote vegetative growth and less in the reproductive period. The requirement of P is high during the flowering stage, which promotes fruit bud formation, flower induction and fruit set. Requirement of K is high during the maturity stage of fruit ripening and quality. Mg requirement is required along with K for sugar translocation and fruit ripening. There is an antagonism effect of K and Mg i.e. excess K suppress Mg. October pruning stage is the stage of flowering, fruit setting and maturity stage, hence for this experiment four fertilizer parameters N,P, K and Mg are considered or estimated.

3.7 Statistical approach for nutrient estimation

This section discusses the method of regression analysis for estimation of N, P, K and Mg nutrients for October pruned data using curve fitting methods using two different softwares. The extracted parameters used in the previous chapter are also extended for this analysis.

Same algorithms discussed in the last chapter were extended to extract the individual parameters R, G, B, H, S, V, I_{kaw}, I_{pca}, etc. for October pruned data. The parameters are extracted with three different thresholds at pixel value 80, 100 and 112. Three different I_{green} indices were obtained with three different thresholds where as other parameters of RGB and HSV color planes along with L, a*, b*, Entropy, I_{ke} and Ipca are calculated at a threshold of 112. These functions and individual parameters are correlated with each nutrient to find a most suitable function for nutrient estimation.

Here in this experiment the two new indices are proposed for nutrient estimation. The first is called as Opponent HSV and second is modified version of equation 8. Opponent HSV is named because HSV values obtained, lies between the range [0 1] and the singular index calculated by subtracting the values of H, S, and V from its maximum value “1” and averaged. As H is represented in angle from 0 to 3600 which is normalized to range 0 to 1, so (1-H) will represent the opposite angle and the same is applicable for saturation and brightness represents the opponent parts. The index OHSV is calculated as shown in equation 8.

$$OHSV = \frac{(1-H)+(1-S)+(1-V)}{3} \quad \text{--------- Eqn 8}$$

Another index, which is a modified version of equation 8 is used to analyze the parameters. Nonlinear mapping of G to R and B is considered with logarithmic function instead of logsig function. It has been observed that newly derived OHSV and Log index gives better correlation with nutrients as compared to other functions if all varieties are considered. To understand the correlation of these parameters with different varieties analysis is carried out and found different results. But the combination of Thompson, Manikchaman and Sonaka (TMS) gave better correlation with these parameters and its correlation compared with all varieties in Table 2.

TMS shows the improved correlation with N, P, K, and Mg as compared to all four varieties. The parameters G, V and L show significant change in correlation with Nitrogen. Index I_{green} I_{g1}, I_{g2} and a* has shown a better correlation with P , Index I_{g1}, I_{g2} and 2G+B/(R-B) has shown significant changes in correlation for K. Parameters B, H, I_{kaw}, I_{as1}, I_{as2} and 2G+B/(R-B) shown the changes in the correlation coefficient for Mg. Newly Derived parameters OHSV and I_{Pk1} and I_{pk2} has shown marginal changes in P and K correlation where as for N and Mg it is considerable. Based on the above formula the Color features extracted for various sample plots with Laboratory values of N, P, K and Mg.

Our research focused on the correlation between nutritional levels and a variety of colour and index-based indicators. To improve accuracy and predictive power, statistical methods such as multiple linear regression and least squares curve fitting can be applied. The association between the dependent variables—nutrient levels—and the independent variables—extracted colour indices—is demonstrated by the regression model. The sum of squared discrepancies between the model's predicted and observed nutrient values is minimised by the use of least squares curve fitting.

Table 2: Color features extracted for various sample plots with Laboratory values of N, P, K and Mg

Plot	**R**	**G**	**B**	**H**	**S**	**V**	**Ikaw**	**Ipca1**	**I_{green}**	**L1**	**a1**	**b1**	**Entrp**	**I_{g1}**	**I_{g2}**	**N**	**P**	**K**	**Mg**
Amarbhingare	168.9833	199.8361	140.4424	0.3175	0.3851	0.8687	0.0942	56.1312	35.6756	99.6628	4.3761	63.3727	7.2049	34.0393	35.2835	1.51	0.47	3.55	0.38
Amogkhed	130.2715	182.0951	108.4684	0.3635	0.5429	0.7916	0.0969	57.9584	84.9266	96.9652	6.8742	69.4685	7.4020	82.1029	84.1467	1.62	0.22	3.90	0.57
Anildabade	126.9584	171.2335	106.9182	0.3659	0.4950	0.7522	0.0876	51.2911	86.4121	95.5192	6.8147	65.4204	7.3113	79.9224	85.3700	1.57	0.36	3.80	0.66
Awatade	135.9033	169.3926	108.7227	0.2990	0.4535	0.7490	0.1107	55.6104	59.5771	99.6740	8.2971	64.5807	7.4801	56.6050	58.3867	1.18	0.23	2.22	0.96
Chandra Mali	127.4378	172.0363	125.5871	0.3996	0.3932	0.7560	0.0094	30.4906	80.3125	97.8848	6.3463	54.8467	7.1427	76.8970	79.8030	1.62	0.29	3.50	0.59
Chunge	144.1499	181.4183	89.7677	0.2850	0.5883	0.7639	0.2412	95.6644	86.0611	93.8115	3.6139	67.7793	7.1137	82.5615	85.6908	1.79	0.28	3.30	0.05
Gangoda	112.4577	172.9204	126.9513	0.4355	0.4628	0.7739	0.0615	35.3942	65.5891	97.8433	6.1076	61.3995	7.4755	61.6050	63.3528	1.40	0.49	2.65	0.44
Ghongde P3	165.9523	189.9981	117.4766	0.3189	0.4888	0.8733	0.1725	80.4609	37.8986	99.6616	15.3349	72.7161	7.5544	35.3886	37.5304	1.57	0.41	3.17	0.35
Kbclone	100.8915	170.0722	127.3617	0.4583	0.5019	0.7618	0.1157	39.5227	68.8194	96.6863	8.8471	70.6370	7.5041	64.4177	67.8170	1.57	0.35	1.80	0.58
Kbmanik	106.08	169.2	128.7	0.46	0.46	0.76	0.0971	36.21	74.22	96.74	8.581	54.71	7.40	68.12	72.37	1.	0.	3.	0.5

	81	439	501	10	43	54		60	26	88	9	39	35	23	08	74	36	50	5
Karamcl one	108.32 16	160.8 626	91.854 3	0.36 66	0.52 98	0.73 39	0.083 4	55.08 07	83.30 81	95.94 32	7.959 2	65.92 00	7.41 75	75.43 11	82.22 38	1. 01	0. 41	2. 15	0.4 6
Karamth om	105.24 34	163.2 538	99.877 4	0.36 45	0.54 62	0.73 88	0.030 6	49.53 44	73.70 62	95.75 70	8.343 0	63.21 71	7.41 14	70.22 14	72.51 11	1. 23	0. 42	2. 30	0.4 2
Anilkash id	134.59 98	173.0 319	108.1 859	0.33 21	0.44 60	0.73 83	0.111 3	57.20 38	93.96 91	94.11 21	4.021 2	59.18 62	6.88 99	90.84 25	93.67 70	1. 51	0. 67	1. 70	0.5 0
Madhuka shid	123.72 91	177.4 256	136.1 219	0.43 08	0.40 11	0.77 26	0.04 57	31.55 98	73.62 31	96.23 51	4.400 2	51.61 94	7.21 09	69.56 79	72.64 68	1. 57	0. 37	1. 50	0.3 7
MaliClo neP2	131.23 39	162.6 920	93.010 6	0.30 20	0.51 95	0.75 99	0.174 0	70.00 03	72.61 52	98.00 43	8.733 2	69.39 53	7.41 83	65.90 51	71.33 76	1. 79	0. 42	2. 35	0.4 9
Malisona kaP3	121.37 35	167.4 783	100.2 054	0.35 41	0.52 20	0.76 05	0.098 7	54.51 18	73.58 13	97.72 34	5.269 6	72.21 97	7.39 07	70.34 59	73.10 70	1. 79	0. 39	3. 50	0.3 5
Moreclo ne	111.66 24	168.3 622	98.810 1	0.35 38	0.55 56	0.75 96	0.065 1	49.89 93	78.79 35	96.65 65	8.444 8	71.98 89	7.46 86	75.22 59	77.85 55	2. 13	0. 53	2. 75	0.4 6
Moretho mson	96.19 96	169.6 084	132.8 271	0.44 77	0.48 55	0.74 26	0.15 98	42.78 83	79.75 90	95.69 75	4.027 7	53.17 47	7.19 28	77.71 54	79.29 83	1. 68	0. 54	3. 20	0.5 0
Sakharec lone	123.85 49	172.2 285	117.9 914	0.36 58	0.41 89	0.74 31	0.027 3	37.95 66	86.36 77	95.67 04	4.939 7	55.34 86	7.07 57	83.87 81	85.88 79	1. 68	0. 55	1. 80	0.4 9
Sakhareg anesh	129.47 41	176.4 880	106.3 664	0.32 35	0.45 87	0.75 29	0.103 0	57.57 22	96.24 23	97.26 85	3.747 4	61.24 20	6.78 49	93.53 05	95.93 00	1. 40	0. 45	2. 65	0.5 2
MSplot1	147.01 40	184.8 179	115.7 944	0.29 83	0.46 95	0.78 49	0.122 6	63.77 02	82.60 73	96.89 15	6.199 0	72.57 52	7.09 68	80.65 35	82.43 23	1. 46	0. 28	2. 20	0.5 2

4 Discussions

4.1 Estimation of nitrogen

Nitrogen requirement as compared to after April pruning is less after October pruning and is an essential nutrient in development stage. Nitrogen has a role in flowering and have an influence on number of vine bunches and weight i.e. ultimately affects yield. Algorithm discussed in figure 1 is applied for extraction of color feature parameters using three color models – RGB, HSV and La*b*.

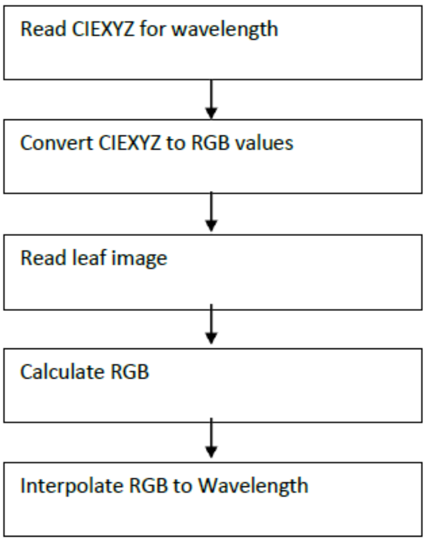


Figure 1: Flowchart for wave length estimation from RGB color image

Color features/ parameters extracted to derive different functions. The correlation coefficient of these parameters and functions are illustrated in Table 3. Table 3 illustrates the correlation with and without illumination effect. Illumination effect is achieved by multiplying the individual parameter or the function by index I_{lx}. Using derived functions regression analysis is carried out and newly developed Opponent HSV (OHSV) function found most suitable for Nitrogen estimation. The individual name indicates a single plot of a single variety.

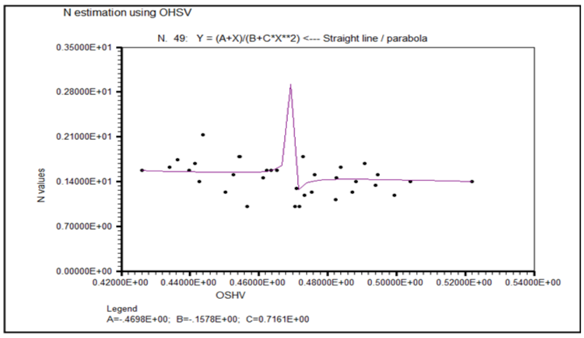
Table 3: Correlation of parameters with P

Parameter	Without I_{lX}	With I_{lX}
R	0.0648	0.2005
G	0.1975	0.2077
B	-0.0892	0.1254
H	-0.1546	0.1047
S	0.0667	0.2282
V	-0.0629	0.1971
I_{kaw}	0.1022	0.1072
I_{pca}	0.236	0.3416
Ig	0.2463	0.2477
L	-0.0687	0.1784

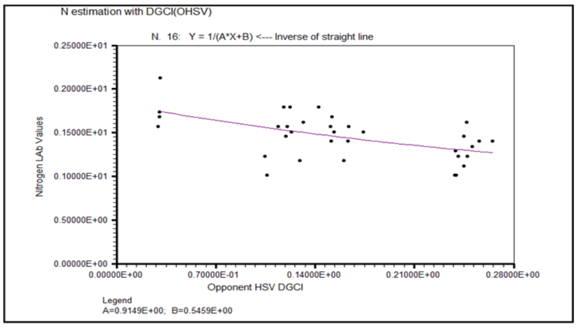
A	-0.1529	0.0745
B	-0.1303	0.1517
Entrp	-0.3035	0.1663
OHSV	0.0311	0.166
Ipk1	0.3815	0.1266

The table illustrates the sample points used in regression analysis for both OHSV function i.e. OHSV with and without illumination effect. Estimated Nitrogen for all 35 samples along with percentage error is also shown.

Figure 2(a) shows the regression for Nitrogen estimation using newly derived function OHSV without illumination effect I_{lx} and Labfit software is used for analysis of regression based on the data in Table 3. Figure 2(b) illustrates the graph of regression analysis for the N estimation using OHSV with illumination effect I_{lx}



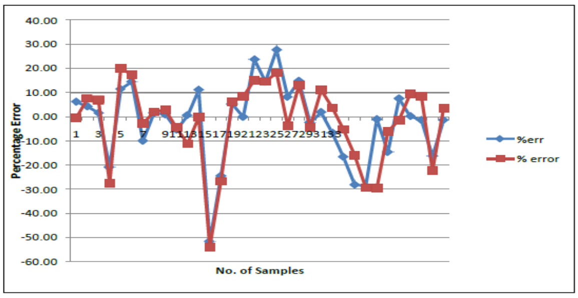
2 (a) OHSV withoutI_{lx}



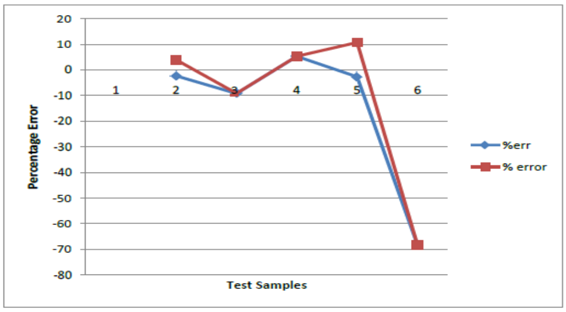
2 (b) OHSV with I_{lx}

Figure 2(a),(b): Regression for N estimation using OHSV withoutI_{lx} and withI_{lx}

Figure 3(a) and 3(b) illustrates the error graph between the values of Laboratory and estimated nitrogen respectively.



3(a) Sample Data



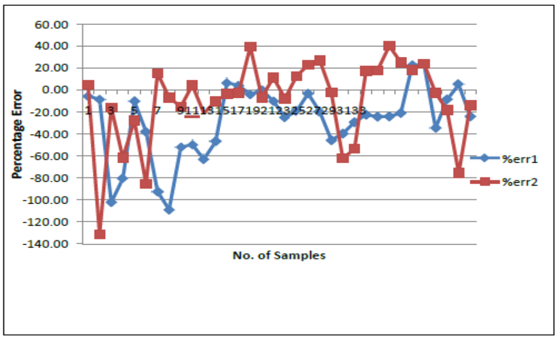
3(b) Test Data

Figure 3(a) and (b) Error graph between Lab and Estimated N for Sample data and Test Data

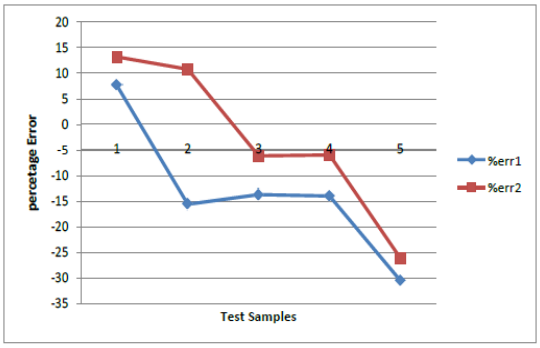
4.2 Estimation of phosphorus

Though the requirement of phosphorus is less than nitrogen and potassium, it plays an important role in seed and fruit development stimulates flowering and have a favorable effect on bud fertility that promotes the yield of grapes. Table 3 shows the correlation coefficient of various parameters obtained from October pruned images. It shows the correlation for both the cases discussed earlier, i.e. the data without effect of illumination and with illumination.

Figure 4(a) shows the regression curve for the first analysis using Matlab software and figure 4 (b) shows the regression curve obtained using the analysis by LAB fit software. Figure 4(a) and 4(b) shows the error graph between the estimated values of P by these two softwares for Sample data and test data respectively.



4(a) Regression Sample



4(b) Test Sample

Figure 4 (a) and (b) Error graph between estimated and Laboratory values of P for regression sample and test sample

4.3 Estimation of potassium (K)

Potassium is needed by grape plants for formation as sugar and starches which is essential for synthesis and cell division. Potassium plays an important role in quality of grapes by controlling its acidity and pH value of the juice. The deficiency will cause the leaves to drop prematurely, resulting in failure of fruit development in terms of color or ripening. Severe deficiency caused unevenly colored small berries and toxicity may induce deficiency of Mg which is known as antagonism effect. A deficiency of potassium leads to susceptibility of grapevine to powdery mildew.

The same algorithm that was applied to previous two nutrients is also used for estimation analysis of potassium. Table 3 shows the correlation of extracted parameters and derived functions which includes newly developed OHSV and I_{Pk1} and I_{pk2} with potassium. Also, it shows the correlation of these parameters and functions when illumination index I_{lx} is taken into consideration.

Table 4 shows the estimation of K using regression analysis. Newly developed I_{pk1} and I_{pk2} both are tested for estimation. Estimation of K using I_{pk1} is carried out by MATLAB and LAB fit whereas I_{pk2} used to estimate K with LAB fit software. These estimated values are indicated as K1, K2 and K3 respectively.

Table 4: Estimation of Potassium using logarithmic index $I_{pk}1$ &I_{pk2}(Sample for Regression)

Ipk1	K	K1	%err Quad		K2	%Err		Ipk2	K	K3	%Err
-0.42114	3.55	2.89	18.68		2.93	17.40		-0.15459	3.55	3.65	-2.83
-0.43678	3.80	2.66	29.96		2.73	28.26		-0.19307	3.80	2.55	32.78
-0.4628	2.22	2.50	-12.59		2.43	-9.37		-0.20981	2.22	2.61	-17.46
-0.46357	3.50	2.50	28.60		2.42	30.86		-0.20725	3.50	2.59	26.09
-0.39183	3.30	3.57	-8.12		3.39	-2.65		-0.15654	3.30	3.53	-7.01
-0.43751	2.65	2.65	-0.13		2.72	-2.52		-0.19166	2.65	2.56	3.39
-0.43799	2.40	2.65	-10.34		2.71	-12.96		-0.17175	2.40	2.88	-19.88
-0.43991	2.77	2.63	5.13		2.69	2.98		-0.17449	2.77	2.80	-1.19
-0.43347	1.80	2.70	-50.07		2.77	-53.77		-0.19245	1.80	2.56	-42.04
-0.44767	3.50	2.56	26.82		2.59	25.86		-0.20146	3.50	2.56	26.98
-0.43278	2.15	2.71	-26.05		2.78	-29.14		-0.20217	2.15	2.56	-18.99
-0.46233	2.35	2.50	-6.39		2.43	-3.53		-0.2172	2.35	2.69	-14.37
-0.43518	3.50	2.68	23.42		2.75	21.54		-0.19626	3.50	2.55	27.20
-0.41441	2.75	3.01	-9.58		3.03	-10.12		-0.18322	2.75	2.64	4.15
-0.43682	3.20	2.66	16.84		2.73	14.83		-0.19487	3.20	2.55	20.32
-0.44458	1.80	2.59	-43.61		2.63	-46.17		-0.19642	1.80	2.55	-41.55
-0.41587	2.65	2.98	-12.62		3.01	-13.47		-0.17549	2.65	2.78	-4.85
-0.41881	2.20	2.93	-33.12		2.96	-34.77		-0.16852	2.20	2.98	-35.47
-0.43062	2.50	2.74	-9.55		2.80	-12.18		-0.1843	2.50	2.62	-4.88
-0.41886	3.10	2.93	5.56		2.96	4.38		-0.17399	3.10	2.82	9.18
-0.40206	3.80	3.29	13.38		3.22	15.34		-0.1613	3.80	3.28	13.75
-0.39491	3.40	3.48	-2.36		3.33	1.92		-0.15442	3.40	3.66	-7.68
-0.41377	3.30	3.03	8.30		3.04	7.95		-0.16894	3.30	2.97	10.12

-0.48481	2.35	2.57	-9.37		2.21	5.85		-0.21646	2.35	2.68	-13.97
-0.45191	2.35	2.54	-7.87		2.55	-8.36		-0.19977	2.35	2.55	-8.55
-0.45421	3.10	2.52	18.59		2.52	18.68		-0.21276	3.10	2.64	14.96
-0.40327	2.30	3.26	-41.81		3.20	-39.03		-0.16766	2.30	3.01	-30.89

From Table 4 it is observed that parameters S, V, functions I_{kaw}, I_{pca}, I_{Pk1} and I_{Pk2} show the positive correlation with potassium with correlation of coefficient R ranging from 0.22 to 0.42. Newly obtained function OHSV show negative correlation with the correlation coefficient value of -0.22. If illumination effect I_{lx} taken into consideration S, V, I_{kaw} and I_{pca} show the marginal changes in coefficient where as I_{pk1} and I_{pk2} shows the significant change in the correlation, i.e. from 0.42 to 0.12. Since all other parameters show the marginal change in correlation coefficient and indices I_{pk1}, I_{pk2} shows significant change, hence I_{pk1} and I_{pk2} are considered for analysis purpose.

I_{pk1} index, which is a newly derived logarithmic index of RGB color parameters used for regression analysis and analyzed with two software MATLAB, LAB fit. Using the MATLAB curve fitting tool, the regression analysis for K, the curve is a quadratic polynomial equation having a coefficient ofdetermination0.2041 with RMSE of 0. 6204.This quadratic equation is represented as equation 9.

$$K_1 = *x^2 + *x + P_1P_2P_3 \qquad \text{----------- Eqn 9}$$

Regression analysis for estimation of K using I_{pk1} with LAB Fit tool have a coefficient of determination, R2 0.1853 and RMSE 0.6084 is represented as equation 10.

$$K_2 = \frac{A}{x2} \qquad \text{-------------------- Eqn 10}$$

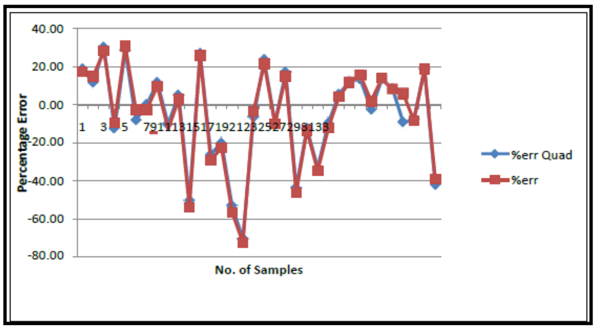
The curve shows the characteristics of the second order hyperbola. The curve has reduced chisquare of 0.31001 and error estimated using this curve have 7 points beyond the range of ±30 percent of sample data and test data. Regression analysis using I_{Pk2} which is a logarithmic function of normalized G gives the best fit curve having a coefficient of determination R2 of 0.2528 and RMSE of 0.601. The curve equation is given by equation 10

$$K3 = \frac{A}{(x + B * (\exp(cx))} \qquad \text{----------- Eqn 11}$$

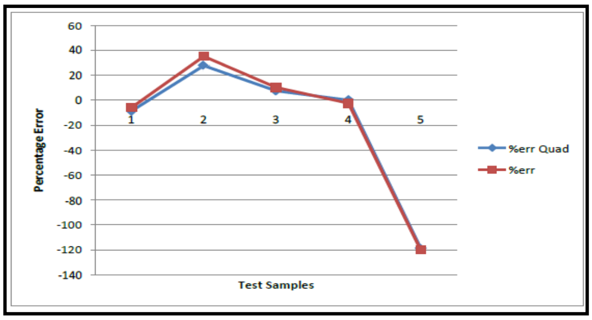
The curve is a mixture of hyperbola and exponential curves which gives the reduced chi-square of 0.361336. The estimation errors for equation 11 have 7 points beyond the range of ±30 percent of sample data and 1 in test data.

The error curves plotted for two different regression analysis are compared with each other as shown in figure 5(a) and 5(b). Figure 5 clearly shows that the error is almost same. The error in test samples shows that the last sample is beyond the boundary of ±30 percent.

The average errors for two regression equations 8 to 10 including sample and test data are -7.07, -6.84 and -7.27 respectively. Though the average error for K2 is less, but estimation samples within error boundary are less compared to K1 and K3. The temperature effect also affects the uptake of potassium.



5(a) Sample data



5 (b) Test data

Figure 5 Error between estimated values (I_{Pk1} and I_{pk2}) of K– Test data

The confidence intervals of the traditional models (CNN, SVM and Random Forest) are compared with the proposed OHSV and IPK1/IPK2) with the different parameters such as accuracy, 95% confidence interval, precision, recall, F1-Score and AUC/ROC are showcased in Table 5. From the table 5, IPK1/IPK2 inferred that the confidence interval lies in the range of 90.8% - 95.2% , which provides the better result among the compared other models. The performance comparison of traditional model with OHSV and IPK1/IPK2 are showcased in Table 6. From it, IPK1/IK2 provides optimal performance when compared with other models.

Table 5: Comparison of Traditional model with the proposed OHSV and IPK1/IPK2

Model	Accuracy	95% CI	Precision	Recall	F1-Score	AUC-ROC
CNN	92%	89.5% - 94.5%	91%	93%	92%	0.95
SVM	85%	82.1% - 87.9%	84%	86%	85%	0.89
Random Forest	88%	85.2% - 90.8%	87%	89%	88%	0.91
OHSV	90%	87.8% - 92.2%	89%	91%	90%	0.93
IPk1/IPk2	93%	90.8% - 95.2%	92%	94%	93%	0.96

Table 6: Performance Comparison of Traditional model with the proposed OHSV and IPK1/IPK2

Method	Accuracy	Precision	Recall (Sensitivity)	F1-Score	AUC-ROC	Advantages
OHSV Index	90%	89%	91%	90%	0.93	Improved color space representation for subtle differences, enhanced tumor region segmentation.
IPk1/IPk2 Indices	93%	92%	94%	93%	0.96	Granular differentiation of glioma regions, highest sensitivity for early glioma detection.
CNN (Convolutional Neural Network)	92%	91%	93%	92%	0.95	High accuracy in deep learning image classification.
SVM (Support Vector Machine)	85%	84%	86%	85%	0.89	Traditional classifier, lower performance in subtle detection cases.
Random Forest	88%	87%	89%	88%	0.91	Versatile but less effective in complex segmentation tasks.

5 Conclusion and future enhancement

Image processing technique has been proved its importance in Agriculture for detection of weeds, yield estimation, nutrient analysis specially nitrogen and chlorophyll estimation, vegetative growth, fruit sorting and pest detection. Combination of feature extractions like color, size and shape with different classifiers has added accuracy to these applications. This research is carried out to study effectiveness of Image Processing for nutrition analysis of grapes.

Nitrogen is related with the greenness of the leaf. Color image processing can be effectively used to estimate the nitrogen using RGB segmentation which leads to I_{green} index I_g. Green index I_g showed better correlation with the nitrogen values obtained by chemical analysis. This index is compared with other indices that are derived by other researchers and it shows the competitive correlation. Regression analysis using statistical technique estimates the nitrogen.

As greenness of leaf is related with the nitrogen content the wavelength estimation of green color of leaf is found to be effective method. This method is cost effective and temperature independent wavelength estimation from RGB parameters correlates to nitrogen. The wavelength and green plane ration have shown better correlation than individual parameters. Regression analysis of wavelength and chemical analysis leads to estimation of Nitrogen directly and linear equation is obtained.

In the future, this work might be expanded to include other crop varieties besides grapes. Deep learning algorithms for feature selection and classification could be implemented, and remote sensing technologies like drone-mounted cameras could be used for large-scale crop nutrient monitoring. This would automate and streamline the process of analysing nutrient content.

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