International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878, Volume-8 Issue-5, January 2020

Predict Growth Stages of Wheat Crop using Digital Image Processing

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Abstract- Manual examination is not as accurate to examine crop growing stages because of the possibility of the human mistake and errors. While machine examination or automatic examination can easily examine crop growing stages and increase productivity because it provides fast and accurate examine result. This study provide a solution to finding the wheat crop growth stages, Once the growing stages are established, farmers can take suitable and measured steps to improve the production of wheat or other agricultural crops. For finding the growth stages of wheat digital image processing technique is used. RGB model, HSI model, mean value of green colour, hue and saturation images use for examining wheat crop.

Keywords: RGB, HSI, Colour Models, Colour Image Processing, Digital Image Processing.

I. INTRODUCTION

In the 20th century, there is a threefold increase in the population of the globe. It is very difficult for us to meet the food demand of the rising population. The development in agriculture is supported by advanced technology. The higher authorities or government's all over the globe square measure according to rising the assembly of some important cereals including wheat, rice, and maize, defrayal massive number of case to confirm the food demand of the nation. Rapidly developing countries like Asia also highly active and they have advance planning for agriculture development in the countries.

Wheat crop is the most cultivated cereal across India. This Rabi crop mature in the winter season. The process of wheat souring is done between October to December. And the same is harvested in the month of February to May. The wheat crop requires chilled winters and hot summer. It is difficult to judge the quality and maturity of the wheat crop but its cultivation is not very difficult.

Manuscript published on January 30, 2020.
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The manual examination is slow, labour-intensive, fallible and tedious. The decision with respect to the age of wheat crops must be carefully examined which was done by an expert and trained farmer. One needs to be perfect in knowledge regarding the quality of fertilizer, herbicide, pesticide, etc. which is highly necessary for a healthy crop. A wheat plant's growth is measured in different stages. Identifying growth stages is very important in order to help farmers to improve their yield. Figure 1 shows different stages of the wheat crop [1] [2].

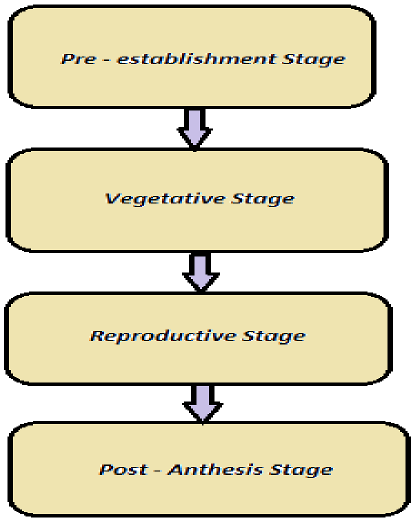


Fig: 1

The first stage is the pre-establishment Stage. It consists of sprouting of seeds by giving rise to seminal roots and the second one is Emergency. Vegetative Stage consists of four stages first one is Seedling Stage. It consists of a large root of young plants. It further differs entailed into one, two, three, four and five-leaf stage. The next one is crown Root Stage. This carried two to four leaves appearance of crown root. The other one is the Tillering stage that starts from the germination of seed into the soil to the appearance of first leaves. The last one is the jointing stage that begins when stalk forms its second node, a hard joint which the plant rises upwards. During this phase, the wheat plant is maximally green.

After the vegetative stage, the next growth stage is the reproductive stage of the wheat plant consist of three types of phases: Booting stage, heading stage and flowering stage. The head of the wheat develops and it becomes apparent during the booting stage. This stage ends with the tips of the head called Awns, begin to grow. The heading stage starts with the appearance of awns from the sheath and Spikes stars emerging out from the leaf sheath.

At last in the flowering stage, this stage consists of Fertilization of ovaries occurs and start to meeting of the seeds. After this stage, the green colour starts decreasing. The fourth stage is post – an thesis Stage. In this stage consist of two types of wheat maturity. Filling stage while and maturity levels. First one Filling Stage. In this stage, the ovaries after fertilization is completed start elongation and transform into seed or ovules passing through milk soft dough and hard dough stages.

Finally, the last one is the Maturity Stage. In this stage colour of the glumes changed and become fairly hard. And moisture gradually reduced the plant. The kernel loses the rest of its humidity during the ripening stage, turns yellow and ready to harvest [3]. Many applications have been introduced to produce numerical descriptions for wheat growth stages. Feekes, Zadoks and Haun scales are very commonly used in wheat crop observation. The Haun scale specifically evaluates the progress of the main shoot. Each new leaf in the first stage is related to the previously produced leaf [4]. The Feekes scale was established at eleven major stages of growth, from seedling to grain maturation. The Feekes scale is used to recognize the ideal stages for chemical treatments, such as fungicides and pesticides. The Feekes scale mostly concentrated on the plant's growth period from the beginning of the stem expansion to the flowering completion.

In comparison, the Zadoks scale offers the most detailed analysis of the wheat plant’s maturity stages. Zadoks uses 10 significant steps of code, which are partitioned and especially ideal for mechanization. Modern scientific practices in farming will increase the monetary margins and enhance the agriculture sector. Depending on nature for better yield, there is still a high-risk probability in farming. Machine learning has emerged as the most fascinating stream of computer science. Machine learning and Digital Image Processing are synonymic terms used frequently, now and then. Finally, a computer system or machine made to learn like human beings i.e. it can think on its own provided if past data, data trends and possible combinations of results are simulated or feed into its system [5]. The advancement of computer science viz. algorithm machine learning, Digital Image processing, etc. ultra-modern technologies can provide a satisfactory solution to some problems concerning with the weather forecast, weeds management, crop harvesting and storage, seed sowing and plant growth, pests protection, product selection, and quality maintenance, etc. few survey are present in these fields such as different field applications, weed detection, yield prediction, crop management, plant stress prediction, disease detection in fruits, disease detection in plants, fruit grading, soil analysis, management zone clustering, water productivity in agriculture[6]. Farmers are dubious about what particular combination of plants to grow in a particular weather regime and on a particular soil giving the highly unrealistic nature of the monsoon. Current agriculture is heavily technology-dependent and concentrated on heavy profits from selected hybrid crop plants which is a long run destroys the physical and biochemical nature of soil [7]. Several coordinated measures can be used for getting optimum yield from the farmland without compromising the fertility of the soil paving the way to sustainable agriculture.

This paper outlines a new approach to predict the growth stages of the wheat crop by capturing a digital image of the crop from time to time. Later on, the collected image data is transferred to a computer. Further analysis of the images was done by using MATLAB 2019b application software. The Wheat crop’s green pigment decreases with age [8]. In the early growth stages, wheat crop is having the maximum green pigments which become minimum at the maturity stage. Therefore, the maturity of the wheat crop analyzed by measuring the percentage of green colour pigment that present in the wheat crop. This measurement of the percentage of green colour that present in the wheat crop is done by using the Digital Image Processing technique.

II. DIGITAL IMAGE PROCESSING TECHNIQUE

Digital image processing has received much attention over the last two decade and for at least twenty-five years, colour has been an integral part of that history [9]. Images are captured, distributed and analysed digitally. Digital image processing is an automated space wherever images are converted to pixels, digitally stored the data and analysed those data using a computer. This significantly reduces costs and improves processing rate and versatility [10], [11]. The digital image processing also enhances the attractiveness of imaging features and can evaluate useful information about the enhanced object scene. Digital image processing transforms and inspects image data based on the features extracted from the input image. Once the digital image is captured, using completely different processes such as image capturing, digitizing the image, noise filtering, and feature recognition [12]. Digital image processing is now being used for medical diagnosis [13], weather forecasts [14], control of food quality [15], and monitoring of galaxies [16]. Face recognition is one of the best-known technology that uses image processing technology [17].

III. COLOUR IMAGE PROCESSING TECHNIQUE

Colour of an organic material provides very important information about that material. Colour models are also known as colour space. Colour spaces are used interchangeably in image processing. However, there is a suitable difference between colour spaces and colour models. Colour space is a mathematical, virtual model and allows creation, representation, reproduction and visualization of colours. Colours are represented as a row of numbers. A set of colours is described as an abstract mathematical model called a colour model. Here we use two colour models one is RGB model and second is HSI model. Colour features colour analysis in this project is predicated on the RGB colour space or RGB colour model and HSI colour model or HIS colour spaces.

A. RGB Colour Model

The most common and obvious colour model is the RGB colour Model. Here we use RGB model for calculate the percentage of green colour in RGB model that helps us to identify the growth stages of wheat.

International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878, Volume-8 Issue-5, January 2020

Fig: 2 RGB Image of stage 1.

Fig: 3 RGB Image of stage 2

Fig: 4 RGB Image of stage 3.

Fig: 5 RGB Image of Maturity Stage.

B. HSI Colour Model

In the HSI model, I stand for intensity and for our purpose it is simply the average of the R, G and b components. The I component specifies the brightness irrespective of the colour H stands for Hue. Hue is an attribute that describes pure colour. Hue is what the artist refers to as "pigment" it is what we think as colour. Yellow, Orange, cyan etc. are example of Hue. S stand for Saturation. This gives us the measure of the degree to which pure colour is diluted by white light. There are four different growth stages of wheat crop [18]. These different growth stages represented with the help of HSI colour space.it show the content of green colour present in each image of different stages.

- **Pre - establishment Stage :**

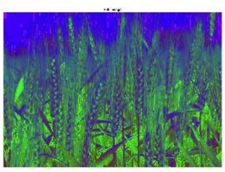


Fig: 6 HSI Image of stage 1.

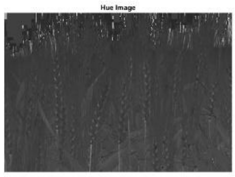


Fig: 7 Hue Image of stage 1.

Fig: 8 Saturation Image of stage 1.

Fig: 9 Intensity Image of stage 1.

- **Vegetative Stage:**

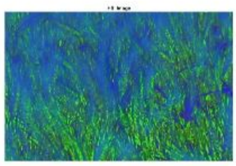


Fig: 10 HSI Image of stage 2.

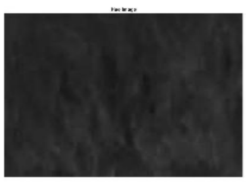


Fig: 11 Hue Image of stage 2.

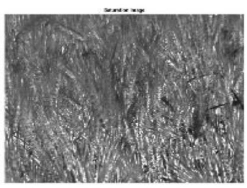


Fig: 12 Saturation Image of stage 2.

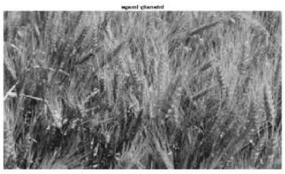


Fig: 13 Intensity Image of stage 2.

- **Reproductive Stage :**

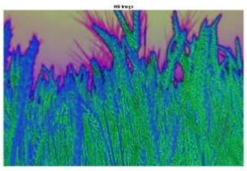


Fig: 14 HSI Image of stage 16.

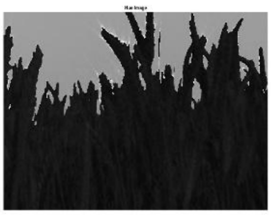


Fig: 15 Hue Image of stage 17.

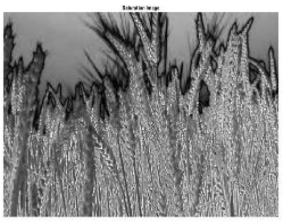


Fig: 16 Saturation Image of stage 3.

Fig: 17 Intensity Image of stage3.

- **Maturity stage :**

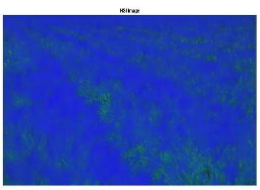


Fig: 18 HSI Image of Maturity Stage.

Fig: 19 Hue Image of Maturity Stage.

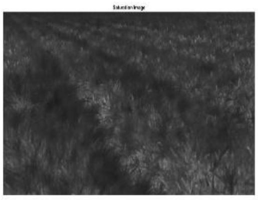


Fig: 20 Saturation Image of Maturity Stage.

Fig: 21 Intensity Image of Maturity Stage.

IV. RELATED WORK

Wheat growth can be broadly divided into different stages. Several machine learning applications have been developed to identify wheat leaf diseases, weed detection in wheat, soil management, water stress management for wheat and may more areas. Best of my knowledge there is no effective and efficient work done to identify the growth stages of wheat using machine learning applications. In this related work I have been cover last three decades work for wheat crop. In very first, Zhang, N. et al. 1995 [19] used shape and geometrical features for weed detection in wheat crop. Several image features like compactness, eight the invariant moments and eccentricity for batter result. In another paper Moshou, D. et al. 2004 [20] developed a system with image spectral reflectance features to detection of yellow rust infected and healthy winter wheat canopies and artificial neural network was used to detection application. Result accuracy of healthy wheat were 98.9% and accuracy of infected yellow rust was 99.4%. Moshou, D. et al. 2005 [21] developed a system to identify yellow rust infected and healthy winter wheat under field circumstances. And artificial neural network is used for detecting yellow. Result accuracy achieved for yellow rust infected wheat 99.4% and accuracy for healthy wheat were 98.7%. In another paper Moshou, D. et al. 2006 [22] developed a system to identify field condition for healthy winter wheat and discrimination of nitrogen, yellow rust infected and also stressed. Artificial neural network and SOM were used in detection system.

Result accuracy for nitrogen stressed were 100% while accuracy for yellow rust infected wheat were 99.92% and accuracy for healthy wheat were 99.39%.In paper Guevara-Hernandez, F. et al. 2011[23] on the basis of external characteristics authors reorganized two grain types using different image features like colour, shape and textural features. The overall result accuracy using selected features property like shape, colour and texture were 99%. Tian, Y. et al. 2012 [24] reorganized leaf rust Pucciniatriticina, pucciniastriformis and leaf blight, powdery mildew leaf diseases in wheat crop. Identification of these leaf diseases authors use wheat image colour, texture and shape features. SVM based multiple classifier system were used for detection, accuracy rate of result 95.16%. Moshou, D. et al. 2014 [25] developed an application to identify water stress detection in wheat crop based on optical multisensory fusion with a least square support vector machine classifier. Accuracy in result, achieved in four categories. First category was control treatment healthy and well supplied with water and its accuracy was 100%. Second category was healthy treatment and deficient water supply and its accuracy was also 100%.Third category was Inoculated treatment with sectorial trifici and well supplied with water and its accuracy was 98.75%. Last category was inoculated treatment and deficient water supply and its accuracy was 98.7%. In another paper Majumdar, D. et al. 2015 [26] developed a detection system for 4 different types of leaves disease using fuzzy clustering algorithms and result accuracy for classification of different diseases were 56%. Olgun, M. et al. 2016 [27] developed an application using K-Means clustering algorithm for grain grading of wheat overall result accuracy was 88.33%. Jiang, G. et al. 2016 [28] developed an application to reorganised weed row detection in wheat crop. This application used k-means clustering algorithm. Weed detection accuracy rate was up to 90%. Mondal, D. et al. 2016 [29] developed an identification application for disease detection on wheat leaves. Author used wheat image features for disease detection on wheat leaves and its accuracy rate was 94% for non-diseased wheat images and 95% for diseased wheat images. Pantazi, X.-E.et al. 2016 [30] developed a system for wheat yield prediction within field variation using artificial neural networks. It is very effective for wheat yield prediction. Yield prediction accuracy rate was 81.65%. the author [31] used EM remotely sensed Red, Green, Blue or RGB Images captured by UAV to identified tomatoes optimal clusters for the Image for determine using Bayesian information criterion. Expectation maximization, K-means, and Self-Organizing Map algorithm were used to categorize pixels into two group Non-tomatoes and tomatoes. UAV stand for unmanned aerial vehicle. Performance of purposed method demonstrated by two representative unmanned aerial vehicle images clicked at different-different height, Author found EM gives batter results then K-means and SOM. Zhang, J. et al. 2017a [32] done work for disease and pest detection. There were several image features used like image colour, image shape and texture. These image features of wheat image were used to prepare a system to reorganize diseases and pest detection in wheat crop production. Its result accuracy rate was 77%. At last Shi, Y. et al. 2017 [33] used spectral features of image for reorganization of diseases and pest detection using spectral image features like MSR, NRI, SIPI, NPCI and many more. Result classification accuracy was 82.9%, 87.9%, 89.2% for three occurrence levels such that slight, severe and moderate. In this paper, In this study author [34] developed a method to determine stage prediction for rice development. This method is based on basic geographic information (obtain from china weather station) and support vector machine. Such kind of study has the potential for feature integration to improve the prediction accuracy and practicability with extensive social and economic factor. In the same year in his first study author [35] provided a tool to discriminate infected by smut fungus Microbotyum Silybum during vegetative growth and healthy Silybum marianum plants. In their second study author present a new system to identify yellow rust infected and healthy, as well as detection of nitrogen, stressed winter wheat. This study helps to accurate detection of fertilizers and fungicides according to the needs of the plant. In same year author [36] presented a system for weed detection which is based on counter propagation artificial neural network (CP-ANN) and as well as unmanned aircraft system for multispectral images captured for the identification of Silybum marianum which is difficult to eliminate and causes major loss on crop yield production. In this same year work also done for disease detection according to author [37] developed a system for the classification of parasites which was based on image processing procedure and the automatic identification of trips in strawberry fruit greenhouse environment, for control in real-time. In this study, work is done to enhance the crop quality according to the author [38] present a method for segmenting the diseased part in the cucumber leaves this system was based on the k-means clustering algorithm. They use five multiclass classification for training to different among seven diseases. The result classification accuracy range was 91.25%. Table.1 and Table.2 contain summery on application of Digital Image Processing and machine learning in wheat crop production.

Table I. Summery on application of machine learning in wheat crop production

Citations	Year	Work	Outcome
[19]	(1995)	Effective criteria for weed identification	Proposed method helps to weed identification in wheat.
[20]	(2004)	Detection of yellow rust in wheat	Helps to maintain the wheat crop quality.
[21]	(2005)	Plant diseases detection	Helps to increase wheat crop yield productivity.
[22]	(2006)	Identify field conditions for healthy winter wheat and discrimination of nitrogen, stressed and yellow rust	Helps to enhance the crop production as well as crop quality.

[23]	(2011)	Extracting the mean spectral reflectance to differentiate on ends in wheat grains	Helps to increase wheat crop yield to the farmers to increase their wheat crop yield.
[24]	(2012)	Recognitions of wheat leaf diseases	Helps to identify diseases in wheat leaf so that minimize the yield loss.
[25]	(2014)	Water stress detection based on optical multisensory fusion	Helps to water management for wheat crop
[26]	(2015)	Classify wheat leaf images to identify rust disease on wheat leaf.	Helps to enhance crop quality of wheat.
[27]	(2016)	Wheat grain classification.	Helps to increase wheat crop yield.
[28]	(2016)	Rows detection of wheat to identify early growth stages.	Helps to enhance crop yield production.
[29]	(2016)	Rust disease detection in wheat.	Disease detection helps to remove the disease so that the farmers enhance crop quality.
[30]	(2016)	Developed a system for wheat yield prediction using ML and advance sensing technique.	Helps to increase wheat crop yield to the farmers to increase their wheat crop yield.
[31]	(2016)	Detection between tomatoes and non-tomatoes images	Easy Identification between tomatoes and non-tomatoes Images
[32]	(2017 a)	Pests and diseases detection in winter wheat.	Helps to enhance crop quality and productivity of wheat.
[33]	(2017)	Reorganization of Pests and diseases detection using spectral image features like MSR, NRI, SIPI, NPCI etc.	Disease detection helps to remove the disease so that the farmers enhance crop quality.
[34]	(2017)	Rice stage prediction for rice development in china	Determine stage prediction for rice development and good for social and economic factor.
[35]	(2017)	Disease detection and nitrogen detection in Plant	Helps to identify diseases detection in early vegetative stage of plant.
[36]	(2017)	Weed Detection	Helps to eliminate major loss on crop yield production.
[37]	(2017)	Vision-based pest detection in strawberry fruit in green house environment.	Helps to enhance strawberry crop production.
[38]	(2017 b)	Disease pixel segmentation and classification	Helps to identify seven types of diseases in cucumber leaves.

Table II. Summery on application of machine learning in wheat crop production

Citations	Year	Technique Used	Result Accuracy Rate
[19]	(1995)	machine vision	Not specify
[20]	(2004)	reflectance measurements and neural networks	accuracy rate of healthy wheat 98.9% and Accuracy rate of infected yellow rust 99.4%.
[21]	(2005)	hyper-spectral and multi-spectral fluorescence imaging using Kohen maps	Accuracy achieved for yellow rust infected wheat 99.4% and accuracy for healthy wheat 98.7%.
[22]	(2006)	ANN/XY-Fusion	accuracy for nitrogen stressed 100% & accuracy for yellow rust infected wheat 99.92% and accuracy for healthy wheat 99.39%.
[23]	(2011)	machine vision system	Result accuracy rate 99%.
[24]	(2012)	SVM-based multiple classifier system	accuracy rate of result 95.16%
[25]	(2014)	least squares support vector machine classifier	achieved in four categories: a) Control treatment healthy and well supplied with water and its accuracy was 100%. b) healthy treatment and deficient water supply accuracy rate 100% c) Inoculated treatment with sectorial traffic and well supplied with water accuracy rate 98.75%. d) inoculated treatment and deficient water supply accuracy rate 98.7%
[26]	(2015)	fuzzy C-means clustering	Result accuracy rate 56%
[27]	(2016)	SVM classifier	Overall result accuracy was 88.33%.
[28]	(2016)	Hough transform and vanishing point	accuracy rate was up to 90%
[29]	(2016)	Pearson correlation coefficient and rough fuzzy C-means	Accuracy rate was 94% for non-diseased wheat images and 95% for diseased wheat images.
[30]	(2016)	machine learning and advanced sensing techniques	Accuracy rate was 81.65%.
[31]	(2016)	Spectral-spatial methods in remotely sensed RGB Images	Overall result accuracy was very good.
[32]	(2017a)	foliar spectral measurements	Result accuracy rate was 77%.

[33]	(2017)	spectral indices and kernel discriminant Analysis	Classification accuracy was 82.9%, 87.9%, 89.2% for three occurrence levels such that slight, severe and moderate.
[34]	(2017b)	SVM Based Model	Accuracy rate was up to 90%.
[35]	(2017)	VNIR field spectroscopy	Accuracy rate was good.
[36]	(2017)	Counter Propagation artificial neural network (CP-ANN)	Overall accuracy was very good.
[37]	(2017)	SVM Classification	Overall result up to 90 %.
[38]	(2017)	K-means clustering algorithm	The result accuracy was 85.70%.

V. IMAGE FEATURES EXTRACTION AND FORMULA USED FOR CALCULATION

Color image processing is used to extracting the Red, Green and Blue colour from the wheat crop image and predict growth stages of wheat crop. As we know the presence of the green color in the wheat crop plant evanesce with its growth development. At very first calculating the presence percentage of green pigment in wheat crop images. After calculating the colour percentage in the RGB images of wheat crop, for the batter result here the RGB colour system (figure 2, 3, 4, and 5 shows respectively all four growing stages of wheat crop) converting into HSI Model. HSI stand for the Hue, Saturation, and intensity. Here very first we converted RGB image data into HIS image data. Figure 6 to figure 21 represents hue, saturation and intensity images, which is converted form of data from RGB image to HSI image for every growing stage of wheat crop. In this process, HSI image represents the image colour analysis, which is based on the Hue value. It is a color attribute, which helps to describe unmixed color (pure color), whereas saturation image describes a measure of the degree to which a pure colour is diluted by white light. The last one is an intensity image that provides the effectiveness of the colors. For colour analysis, the three-dimensional RGB pigment converted into a one dimensional 'H' space.

The color component and amount of hue in the image can be represented with the help of histogram for digitized colour image. In this work, we are taking four images of different stages (stage1, stage2, satge3, and stage4 or maturity stage) of wheat crop at different instances of time. The stage1 is taken after 55 days of sowing wheat. Stage 2 is considered after up to 60 weeks or 426 days of sowing and the stage3 image is taken after up to 74 weeks or 518 days older and maturity stage image is taken after 79 weeks or 553 days. Time to time wheat crop requirements can be changed and at the growing age of eight, fourteen and eighteen weeks, the wheat crop show maximized variation in the requirements [39] [40] [41].

After knowing this growth phase of wheat crop farmers can take appropriate steps and cultivate better yield production. For identifying these phase we use HSI images as well as we calculate mean values of red, green and blue colour by using colour image processing in digital image processing. MATLAB is used for digital image processing. Mean value of Red, Mean value of Green and Mean value of blue colour describe as meanR, meanG, and meanB respectively. This computational helps to comprehend the most dominant primary colour of images.

Fig: 22 stage 1.

Fig: 23 stage 2.

Fig: 24 stage 3

Fig: 25 maturity stage

A. Formula used for Calculation

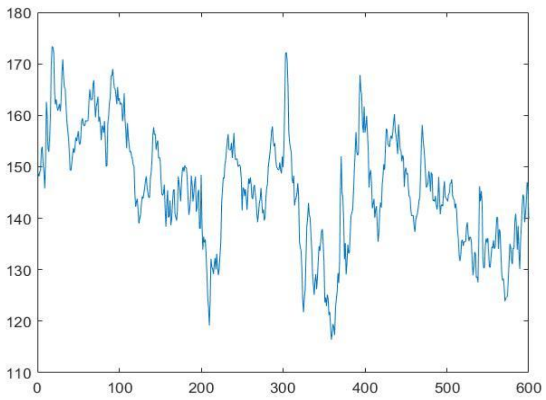
Presence of Green colour percentage in RGB modal,
GreenValueInRGB = (g*100). /(r+g+b);
Formula used to calculate Hue, Saturation, Intensity value:

- **Hue value**
  Formula used for calculate hue value in HSI model. Here Hue is represented by using H Alphabet letter.
  Hue (H), $\tan(H) = \frac{\sqrt{3}(g-b)}{r-g-b}$
- **Saturation value**
  Formula used for calculate Saturation value in HSI model. Saturation is represented by using S Alphabet letter.
  Saturation $(S) = 1 - \frac{3}{r+g+b}[\min(r, b, g)]$
- **Intensity value**
  Formula used for calculate Intensity value in HSI model. And Intensity is represented by using I Alphabet letter.
  Intensity $(I) = (r+g+b)/3$;

VI. RESULT AND DISCUSSION

Our findings appear to be well substantiated by colour image processing. The corresponding images showing the green colour content present in four different stages of wheat crop. Although, it is quite difficult to identify the content of green colour in subsequent graphs. Therefore, we determined the mean of three colours present in each graph by separating Red, Green, and Blue color. Here, Mean of Red, Green, and Blue is represented as meanR, meanG, and meanB respectively.

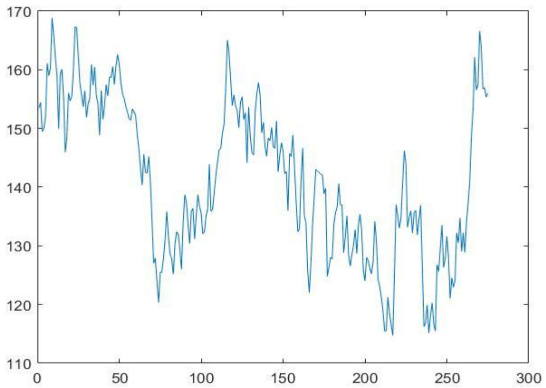
- **Mean of Green colour of stage 1**



Column Number

Fig: 26 Column wise mean of green colour of stage 1.

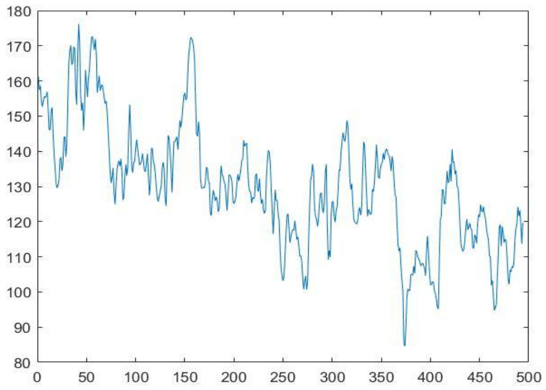
- **Mean of Green colour of stage 2**



Column Number

Fig: 27 Column wise mean of green colour of stage 2.

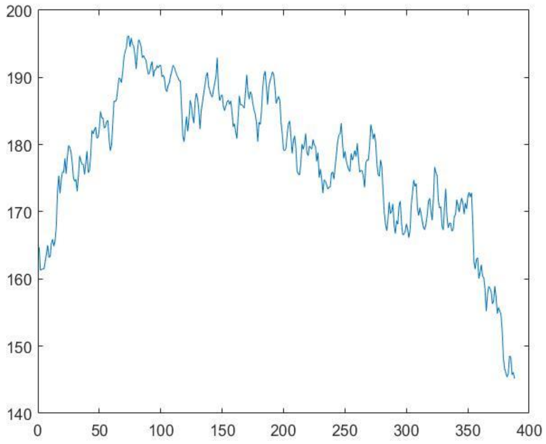
- **Mean of Green colour of stage3**



Column Number

Fig: 28 Colum wise mean of green colour of stage 3.

- **Mean of Green colour of stage 4**



Column Number

Fig: 29 Colum wise mean of green colour of Maturity stage.

In the above four graph, we plotted mean of green color for four maturity stages of wheat crops; stage 1, stage 2, stage 3, and stage 4 respectively. The graphs above also reveal that the mean range of green color is maximum in the first stage, moderate in the second and third stage, and the range is least at the maturity stage. Based on the formulas‟ mentioned in this paper along with RGB values, the percentage of Green color, Hue, saturation and Intensity were obtained for the four maturity stages of wheat crop. The experimental analysis showed that the Green color percentage is decreasing from the first stage to the maturity stage which reveals that stage 1 has a maximum Green color and the maturity stage or stage 4 has the least Green color. Green colour percentage in image shows that stage one is an initial stage which is younger than other stages because it has a high percentage of green colour as comparative other stages figure 26 shows it very clearly.

Here, the HSI color model are used for identifying growth stages of wheat crop. Each level gives distinct values for Hue, Saturation, and Intensity component. For level, one hue is maximum and reduce with the growth of wheat crop and the same as saturation level also reduce with growth of wheat crop. And also intensity also maximum for level one and reduce the same as hue and saturation. Hue, saturation and Intensity components give distinct values for vegetative (stage 2) and reproductive stage (stage 3). The above images show that the growth of crop is increases and values of H, S, and I decrease. The maturity level contain a minimum percentage of green colour and minimum percentage of Hue, Saturation, and Intensity. The future of agriculture demands automation in farming and digital image processing plays a very effective and Innovative role in investigation the crop cover. Colour image processing is a powerful tool in digital image processing which plays a vital role in precious advance farming [22].

When the crop plant requirements do not meet due to a shortage of essential nutrients in it, the colour of crop change.

Colour is a vital aspect to invigilate the health of the plant crop and by observing the crop colour, the crop health can be predicted. Similar as we use colour aspect to predict growth stages of wheat plants. Colour image processing is used to predict growth stages of wheat crops using colour aspect of the plant crop. Image processing techniques can be used in several areas of agriculture like observing the health of the crop and investigate disease in the crop field and take appropriate action to ensure batter yield [23].

VII. CONCLUSION

Manual examination is not as accurate to examine crop growing stages because of the possibility of the human mistake and errors. While machine examination or automatic examination can easily examine crop growing stages and increase productivity because it provides fast and accurate examine result. The magnificent yielding of the crops depend upon vital growing phases so that during the growing season, the plant can be capitalized on suitable weather conditions. However, an understanding of the crops can contribute to the assessment of crop conditions and production potential during the growing season. This paper evaluates four different images of wheat at different intervals. It was certainly taken as changes in crop nutrition that change in the demand for fertilizer and other nutrients with crop production. The color processing technique is used to determine the growth stages of wheat crops and according to that growth stage, required actions can be taken. Once the growing stages are established, farmers can take suitable and measured steps to improve the production of wheat or other agricultural crops.

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