

Prognosis of Lush in Rice Crops and Nourishing Inadequacy by Exerting Multiclass SVM Through GPS

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Abstract- This system mainly focus to increase the productivity of rice crops which is one of a critical problem that the farmers are facing. Using Php code this study helps to connect globally the farmers through online-Global Positioning System and know their productivity and problems that they face during production. Images of rice crops captured by the farmers with the very short duration of rice growth period is uploaded. The LAB values are determined for the captured image. Clustering and segmentation is done for the images to separate the foreground and background of the image. These values are compared with the pre-estimated Nitrogen(N) values that are obtained using (leaf color chart) LCC. Multi class support vector machine(MSVM) is used to procure the amount of Nitrogen values to be tacked on to make the crop lushier. Based on the N value status the amount of urea to be added is determined. When the farmer capture picture of the rice crops, the amount of N present in it will be displayed on the screen.

Keywords : Production, Rice crops, ICT

I. INTRODUCTION

Rice is the staple food of Asia and part of the Pacific where 90 percent of the world's rice is produced and consumed in the Asia-Pacific Region with growing prosperity and urbanization, per capita rice consumption has started declining in the middle and high-income Asian countries but nearly a fourth of the Asian population is still poor and has considerable unmet demand for rice. It is in these countries that rice consumption will grow faster.

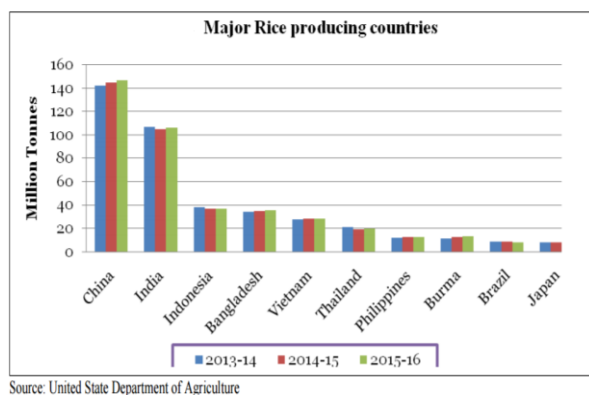


Fig.1.1. Production of rice in major rice producing countries in the year 2013-16

Duration groups in rice

- Very early About 100 days
- Short 100-120 days
- Medium 121-140 days
- Long 141-160 days
- Very long Above 160 days

From the below tables it is evident that the productivity in rice crops should increase as the population is increasing. Yield decline is noticed when in order to get the same yield level, increased amounts of inputs are needed. Yield decline may occur when management practices are held constant on intensive irrigated rice systems, owing to changes in soil properties and improper nutrient balance.

II. LITERATURE REVIEW

In the year 2006, Daniela Stroppiana et.al [8], implemented the remote sensing techniques for monitoring crop conditions and assessing nutrition requirements for implementing sustainable agriculture. [1]Remote sensing techniques are a unique way to acquire information on vegetation conditions over large areas to be used as forcing variables within simulation models. The results indicate that rice reflectance is significantly influenced by nitrogen supply at certain wavelengths. [2]Regression analysis highlighted that the visible region of the spectrum is the most sensitive to plant nitrogen concentration when reflectance measures are

combined into a spectral index. [3]An automated procedure was done to analyse the possible wavelength combinations to derive a Normalized Difference Index (NDI) correlated to Plant Nitrogen Concentration (PNC). The derived index, which appeared to be least influenced by plant biomass and Leaf Area Index (LAI), and the Simple Ratio (SR) index, widely used as an indicator of vegetation conditions, have been spatialized over the experimental field. The output maps have been discussed in terms of ability in describing the spatial variability of Aboveground Biomass (AGB) and PNC. [11] Features extracted for a perfect action implementation[4]The analysis of the correlation between single band reflectance and N concentration confirms previous findings and showed a weak prediction ability over the visible and near-infrared spectrum range. This approach exploited the hyperspectral property of the spectroradiometer used for field data acquisition. [5]The output maps confirm previous results: indeed, they show different patterns due to a different spatial variability of the biophysical variables. [6]The maps, obtained with proximal sensing techniques, highlight the potential of radiometric (remotely and proximal sensed) data for regional vegetation monitoring.

Gholizadeh et.al [9], in the year 2009 proposed a method to measure plant nutrient variability and the information made known to the farmers before the new season starts.[7]Measurements of rice SPAD readings and nitrogen content were obtained in a Malaysian rice paddy field. SPAD reading data was manually collected on 80DAT and measured using a Minolta SPAD 502. Leaf samples were collected at 60 points at the same time to compare results from sampling with SPAD reading values. Samples nitrogen content was analyzed in a laboratory. Analysis of variance, variogram and kriging were conducted to determine the variability of the measured parameters and also their relationship. SPAD reading and nitrogen content maps were created on the interpretation of the data was investigated. Final result indicated that SPAD readings are closely related to leaf N content which means the potential for technology of precision farming to understand and control variation in Malaysian production fields and also SPAD chlorophyll meter ability to monitor the N status of rice and recommend the amount of N fertilization. Semivariogram showed high sampling error and stronger spatial dependence on 80DAT. Descriptive statistics, semivariance analysis and point kriging were employed to determine the variability maps in the measured parameters. Savithri et.al.,[10] A Prediction on the fertile nature of crops In the delta regions of TN. M.M.Ali et.al [1], in the year 2013 proposed a new, easy to use and non-destructive diagnostic approach to detect plantCh and N levels using an image processing technique is developed using the RGB (Red, Green and Blue) colour model.

III. METHODOLOGY

The productivity of rice crops can be increased by determining the amount of nitrogen content present in the rice crops.

3.1 Description of the approach:

Below is the block diagram of the proposed methodology which gives us a brief introduction of the blocks that are used in implementation of the system.

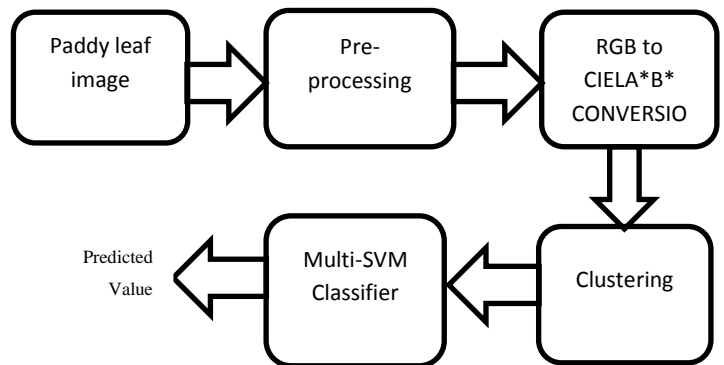


Fig 3.1. Block Diagram

3.2 Rice crop images:

The crop images are captured from the field. The images of the crop were captured during 3 stages of the total harvest period. We have done the prediction of nutrient in the crops for the duration - very short period (40-100days). The Nitrogen (N) will be added at 2 stages for very short period duration. The days after which the N content (urea) will be added are:

- 1)After 30 days of the panicle initiation.
- 2)After 40 days of the panicle initiation.

Finally the harvest will be done after this span of 40 days. A set of images were captured during the 15th day after panicle initiation of rice crops. We captured the images after 15th days because to ensure the growth of the crops at the initial stages and to predict the N content at that stage. The next span of images was captured during the 35th day to ensure the variation in the N content after applying urea. Based on these variations the amount of urea to be added is predicted and is used wisely. Nearly 50 – 100 images were captured.

3.3 Leaf color chart (LCC):

Leaf color chart is a chart that has the variations of green shades in it to predict the amount of N present the crops. The Leaf Colour Chart (LCC) is used to determine the N fertilizer needs of rice crops. LCC has four or six or eight green strips, with colour ranging from yellow green to dark green. It determines the greenness of the rice leaf, which indicates its N content.

The 6 panel leaf colour chart (Fig 3.1 - as shown below) is used in our project. The values of different classes (1 – 6) are identified and is used in the training phase. The color shades are classified into six classes. The 1st class means that the N content is very low and the 6th class means that the crop has sufficient N content. LCC critical value is 3.0 in low N response. When observations show less than the critical color value, N can be applied:

@35kg N/ha in dry season
 @30kg N/ha in wet season per application per ha.

The amount of urea should be added in proportionate. If urea is added beyond the need then the yield decreases and hence affects the productivity of the rice crops.

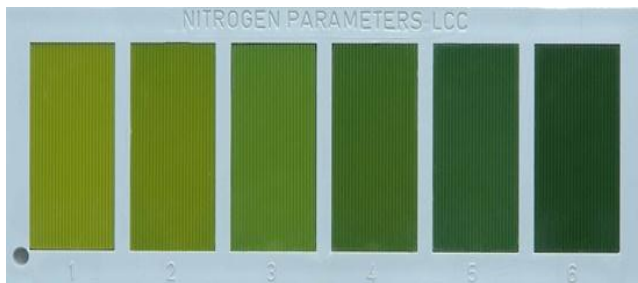


Fig-2 – Six panel Leaf color chart.

3.4 LAB conversion

The captured images are converted into LAB and the values are obtained. In LAB L, A and B stands for:

L: Lightness
 A: color opponent green–red
 B: color opponent blue – yellow.

3.5 K-means clustering:

Image clustering is done to detect only the crop leaf (green or yellow) color for accurate prediction. **k-means clustering** is a method of vector quantization, originally from signal processing, that is popular for cluster analysis in data mining. **k-means clustering** aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster. This results in a partitioning of the data space into Voronoi cells.

3.6 Support Vector Machine (SVM) classifier:

The images are tested and trained using Multi class Support Vector Machine (MSVM). About 50 – 75 images were trained. The L, A & B values of the captured rice crop images were compared with the pre-determined LCC values. The LCC is grouped into six classes. Different class specifies different N values. Now the captured image is compared with this pre-conceived LCC chart value and the testing is done. Finally the class into which the image falls is determined and

based on the result analysis on the amount of urea to be applied is calculated.

In machine learning,

3.7 Kernel machine

The kernel machine used in our proposed system is Radial basis functions kernel (RBF). In machine learning, **kernel methods** are a class of algorithms for pattern analysis, whose best known member is the support vector machine (SVM). The general task of pattern analysis is to find and study general types of relations (for example clusters, rankings, principle components, correlations, classifications) in datasets. For many algorithms that solve these tasks, the data in raw representation have to be explicitly transformed into feature vector representations via a user-specified *feature map*: in contrast, kernel methods require only a user-specified *kernel*, i.e., a similarity function over pairs of data points in raw representation.

Kernel methods owe their name to the use of kernel function, which enable them to operate in a high-dimensional, *implicit* feature space without ever computing the coordinates of the data in that space, but rather by simply computing the inner products between the images of all pairs of data in the feature space. This operation is often computationally cheaper than the explicit computation of the coordinates. This approach is called the "**kernel trick**". Kernel functions have been introduced for sequence data, graphs, text, images, as well as vectors. Algorithms capable of operating with kernels include the kernel perceptron, support vector machines (SVM), Gaussian processes, Principle component analysis (PCA), canonical correlation, ridge regression, Spectral clustering, Linear adaptive filtering and many others. Any linear model can be turned into a non-linear model by applying the kernel trick to the model: replacing its features (predictors) by a kernel function.

Most kernel algorithms are based on convex optimization or Eigen problems and are statistically well-founded.

3.8 Radial basis function kernel:

In machine learning, the (**Gaussian**) **radial basis function kernel**, or **RBF kernel**, is a popular kernel function used in various kernelized learning algorithms. In particular, it is commonly used in support vector machine classification.

3.9 Multiclass SVM

Multiclass SVM aims to assign labels to instances by using support vector machines, where the labels are drawn from a finite set of several elements. We have used six classes of color variations hence for accurate results we have trained the data set using Multi-class SVM.

The dominant approach for doing so is to reduce the single multiclass problem into multiple binary classification

problems. Common methods for such reduction include Building binary classifiers which distinguish

(i) between one of the labels and the rest (*one-versus-all*) between every pair of classes (*one-versus-one*). Classification of new instances for the one-versus-all case is done by a winner-takes-all strategy, in which the classifier with the highest output function assigns the class (it is important that the output functions be calibrated to produce comparable scores). For the one-versus-one approach, classification is done by a max-wins voting strategy, in which every classifier assigns the instance to one of the two classes, then the vote for the assigned class is increased by one vote, and finally the class with the most votes determines the instance classification.

- (i) Directed acyclic class SVM (DAGSVM).
- (ii) Error-correcting output code.

Crammer and Singer proposed a multiclass SVM method which casts the multiclass classification problem into a single optimization problem, rather than decomposing it into multiple binary classification problems.

Code:

```
function [itrfin] = multesvm( T,C,test )
svmStruct =
svmtrain(T,newClass,'kernel_function','rbf');
svmStruct = svmtrain(T,newClass);
classes = svmclassify(svmStruct,tst);
```

IV. RESULTS AND DISCUSSIONS

The mentioned blocks in the proposed methodology are connected and implemented. On implementing the blocks, the results that are obtained and accuracy of the trained and tested algorithm is discussed in this chapter.

The testing and training of the algorithm is done. Nearly 50 - 75 images were captured and is given as input to the classifier for training and testing. The rice crop images were captured using digital camera with resolution 13MP (daylight) and are fed in as input to the multiclass support vector machine (MSVM). The sample rice crop images were captured in 2 different fields. A field in Kanchipuram district and the other one in Thiruvallur district. The season - duration of the rice crops grown in both the fields is very short duration period. The images captured at Kanchipuram district exhibited medium to high nitrogen content while the images captured at Thiruvallur district field exhibited low to medium nitrogen content.

The LAB values for captured image is determined and then the foreground and background is separated by using K-means clustering and then classified. The corresponding class

of the image in Leaf color chart is determined. Based on the class the amount of Nitrogen to be sprinkled is estimated.

Input images:

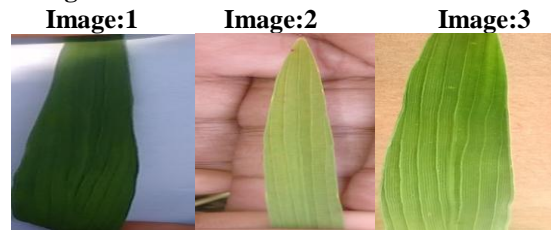


Fig.4.1.Sample image-1, image-2, image-3

Fig. 4.1 is the sample input image -1 that is captured and given as input to the classifier. The nitrogen content when calculated manually using leaf color chart is observed to be 4. Fig. 4.2 is the sample input image- 2 that is captured and given for testing and training of the algorithm. The nitrogen value exhibited by this crop image when determined manually using leaf color chart is 1. Fig. 4.3 is an other sample image that was captured and given as input. The nitrogen value exhibited by this crop is found to be 2.

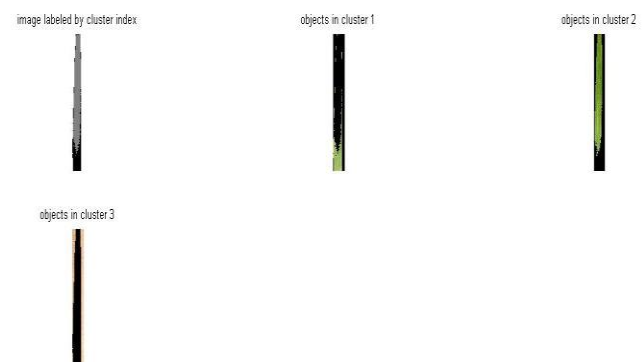
LCC Output for image 1:



Fig.4.4 LCC Output for Image 1.

Fig. 4.4 is the LAB values of LCC for Image 1. The image belongs to LCC class 4.

Clustered image:



```
>> multisvm2
LEAF BELONGS TO LCC CLASS:
4
LEAF STATUS:
HEALTHY LEAF
fx >>
```



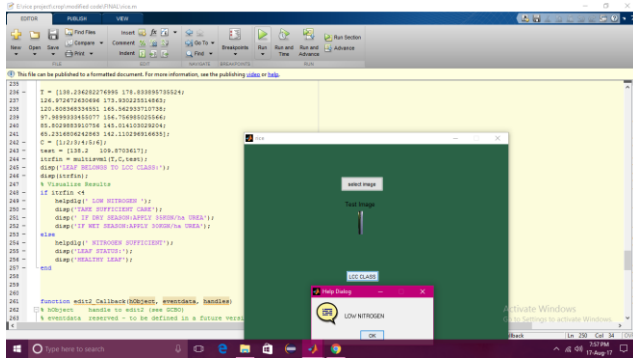
Fig.4.5.Clustered image. , Fig.4.6 Multiclass SVM output.

Fig.4.5 shows the clustered output of the input image. The clustering is done to separate the foreground and background of the image. Each time when executed the region of interest (ROI) is to be specified for clustering the image. Finally the output is obtained as above.

From the obtained cluster image the LAB values are determined. The L and B parameter values are then given as data set of text image in the algorithm. The trained set is the preset value that is obtained from the leaf color chart (six classes). Finally the output will be displayed as above (Fig. 6) where the amount of nitrogen present is specified and the required measures to be taken to make the crop luster.

As discussed in the previous chapters, six panel LCC is used for manually predicting the amount of N present in our project. These values are pre-estimated and tabulated. The processing is done and is automated where the system will predict the class of LCC in which the rice crop falls.

The clustered output for input shown above. The L, A and B values are determined and is saved. These values are given in as input for training and testing data in multi class support vector machine (MSVM).



The class of LCC under which the selected rice crop falls is obtained and the amount of urea to be added to make the crop more fertile and to increase the amount of N content in it is also specified.

Performance Analysis:

This table shows the value that we obtained manually using the LCC and B values during the testing and training from the system. Table shows the L and B parameters of the image also the predicted class value (input image 1). The trained value is again 3 which match the predefined value. L and B parameters are used in training the image in Multi class SVM.

For image-2 the predefined value is found to be 1 (from table- 4.1). The trained value is also 1. From Fig.4.10 we can state that the N value is very low and the amount of urea to be added to make the crop fertile is:

- In dry season: 35KgN/ha
- In wet season: 30KgN/ha

When the value is greater than 4 then it means the nitrogen present in it is sufficient.

For the input crop image- 3 the tested output is found to be 1. It contradicts with the value that was obtained by us using Leaf color chart. The manually determined value is under class 3.

ACCURACY

The table below shows the accuracy that is obtained when the classifier is trained and tested. The tables specifies the total number of images that were taken for training and testing and the number of tests that specified the incorrect lcc value. The ratio of values that showed incorrect values to the total number of images considered for training and testing * 100 gives the accuracy of the proposed system.

Total number of Images	No of images with correct output	No of images With incorrect output	Accuracy
56	40	16	.7142

Table.Accuracy rate

According to table 4.2 the number of LCC values in the trained data set that were obtained to be same when compared with pre defined value is found to be 40/56 images (Considering LB parameters).

Accuracy = 40/56 = .7142.

Therefore, the total accuracy is found to be 71.42%

V. CONCLUSION

The proposed methodology helps to solve the problem and the desired output obtained. When the rice images are captured and are given as input to the MSVM, it will automatically state the N status in the rice crops. The system works accurately with less cost. Time complexity also reduces. The constraints faced by us during the capturing of the image are the variations in light intensity as we captured the images during the day time. To overcome the constraint we used LAB values that reduce the light intensity. This methodology can be extended to other crops and can be given as input to the industry.

REFERENCES

[1]Ali M.M, Ahmed Al-Ani, Derek Eamus& Daniel K. Y. Tan. (2013), ‘An Algorithm Based on the RGB Colour Model to Estimate Plant Chlorophyll and Nitrogen Contents’, International Conference on Sustainable Environment and Agriculture IPCBEE vol.57.
 [2]Alagurani.K , Suresh S , Mrs. L. Sheela (2014),’ Maintaining Ecological Integrity: Real Time Crop Field Monitoring Using Leaf Colour Chart’, International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, Vol. 3.

- [3]Amandeep Singh, ManinderLal Singh. (2015), 'Automated Color Prediction of Paddy Crop Leaf using Image Processing', IEEE International Conference on Technological Innovations in ICT for Agriculture and Rural Development.
- [4] Ali M.M, Ahmed Al-Ani, Derek Eamus& Daniel K. Y. Tan. (2016), 'Leaf Nitrogen Determination Using Non-Destructive Techniques – A Review', Journal of Plant Nutrition.
- [5].ArtiSingh,BaskarGanapathysubramanian,Asheesh Kumar Singh, and SoumikSarkar. (2016), 'Machine Learning for High-Throughput Stress Phenotyping in Plants.' , Trends in Plant Science Vol. 21, No. 2
- [6].Chetna V. Maheshwari.(2013),' MACHINE VISION TECHNOLOGY FOR ORYZA SATIVA L.(RICE)',International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering , Vol. 2.
- [7].Chen L.S, K. Wang, (2014), 'Diagnosing of rice nitrogen stress based on static scanning technology and image information extraction', Journal of Soil Science and Plant Nutrition,14(2), 382-393.
- [8].Daniela Stroppiana1, MircoBoschetti, Pietro Alessandro Brivio, Stefano Bocchi.(2006),' REMOTELY SENSED ESTIMATION OF RICE NITROGEN CONCENTRATION FOR FORCING CROP GROWTH MODELS', Italian Journal of Agrometeorology 50 - 57 (3).
- [9]. Gholizadeh, M.S.M. Amin, R. Aimrun.(2009),' Evaluation of Leaf Total Nitrogen Content for Nitrogen Management in a Malaysian Paddy Field by Using Soil Plant Analysis Development Chlorophyll Meter', American Journal of Agricultural and Biological Sciences 4 (4): 278-282.
- [10].Dr.Savithri.V, Anuradha.G(2015),' A Prediction on the fertile nature of crops In the delta regions of TN, Australian Journal of Basic and Applied Sciences,9(20), pg. 559-566.
- [11] Dr.V.Savithri and Ms.RasigaBalasubramani, "Object Features Extracted for a Perfect Action Implementation" International Journal of Scientific Engineering and Research(EUROPE) 7(6), pp.808-812.

Authors Profile

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