Identification of Maize from Multi-crop Drone Images using Machine Learning Techniques

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***Abstract*— Maize is the second most important crop for North Eastern Region (NER) in terms of acreage and production. However, there is a lack of authentic statistics on maize acreage in the region. In view of that, an attempt has been made for the identification of maize crop in multiple crop areas using drone images with Machine Learning (ML) techniques. Traditional supervised algorithm viz. Maximum Likelihood Classifier (MLC) and advanced ML algorithms viz. Support Vector Machines (SVMs) with appropriate kernel parameters and Multi Layer Perceptron (MLP) were employed for classification and identification of maize crop. The drone was flown at 120m height with 12.4 Megapixel camera over the multiple crop areas of Darrang district, Indian state of Assam, to capture the high-resolution images. The SVM classifier was used under different kernel configurations to assess the predictive ability and time complexity. Four kernel parameters viz. linear, polynomial, Radial Basis Function (RBF) and sigmoid have been utilized in SVMs. It was observed that SVMs with polynomial kernel achieved the highest predictive accuracy (OA=82.29% and KIA=0.78) with comparatively minimal computational cost (Time =05.26 sec) than RBF (OA=77.39%) followed by sigmoid (OA=73.37%) and Linear (OA=70.33%) in terms of overall classes and maize crop class classification. MLP with three hidden layers registered comparatively less accuracy (OA=78.24%) than SVMs with polynomial kernel and also it is very expensive in terms of computation cost (247.45 sec). MLC does not perform well on the high-resolution drone data and scored less overall accuracy (OA=66.76%) than SVMs and MLP. SVMs were found to be appropriate for identification of maize crops from drone images as they require minimal training samples than MLP and MLC.**

Keywords*— *Crop Identification, Maize Crop, Classification, Drone, Machine Learning.

I. INTRODUCTION

Crop identification and classification is a fundamental task in precision agriculture that would not only provide the correct and timely information about the crops and but also plays an important role to generate the crop type maps those are key inputs for up to date agriculture statistics, crop yield estimation and forecasting. Maize (Zea mays L.) is nutrient-rich and most versatile promising crop showing wider adaptability under different agro-climatic environment [1]. In 2015-16, India has sown maize crop in 8.69 million hectares of agricultural land and received crop yield of 21.81 million tons that contributed 9% of total food grain of the country. In the North Eastern Region (NER) of India, despite receiving adequate rainfall and rich availability of carbon content in the soil, average yield production of the maize crop is significantly low (less than 1.50 tons/hectare) than rest of the country. Small farming land patches of maize crops, shifting cultivation and unavailability of timely satellite data due to unfavorable weather conditions in the region are the major problems in order to segregate spectrally similar crops. The low spatial and temporal resolution also creates problems in extracting effective features from the crops in multiple crop areas in order to identify a single crop [2]. Coarse and moderate resolution satellite data is affected by mixed pixel problems that lead to the low predictive accuracy of a classifier [3]. In contrast, drone images offering thematic information at ultra-spatial resolution than satellites have knocked the door of Remote Sensing (RS) community for various applications including crop identification and classification. Drone imageries with the centimeter-level spatial resolution are creating new paradigms to improve the identification capability of a Machine Learning (ML) algorithm of various spectrally same land surface objects [4-5]. Regardless of the great potential, there are few challenges and limitations with drone imaging including limited accessibility of the area, endurance, and short flight time, etc. From the data processing perspective, the ultra-spatial resolution images acquired by drone generally affected by noise due to amplified detectable objects when traditional pixel-based techniques are applied for classification [4-6]. From a data collection and availability perspective, it is not always possible to acquire data on demand in the region due to inadequate access to the farming lands and unfavorable weather conditions. Therefore, there is a prerequisite need to increase the classifiers predictive ability using advanced ML techniques where a minimum number of training samples and single date imageries are available for specific crop identification [7-8].

ML techniques are being utilized in the classification of RS satellite and drone data including crop identification to achieve higher classification accuracy [10-14]. Numerous studies focusing on crop classification and identification using space and aerial-based technology including RGB (Red, Green, Blue) images with ML techniques can be found in [15-19, 24-26]. It was reported that [20], maize crops were identified from multiple crop areas including sugarcane, wheat, pea, lentil, mustard in Indian state of Uttar Pradesh with 88.9% overall accuracy using an Artificial Neural Network (ANN) on Linear Imaging Self Scanning Sensor (LISS) - IV and Landsat 8 satellite data. It was indicated that the learning rate and the number of iterations are the important parameters in ANN so far stability of the classification performance are concerned. Elmansouri L. 2017 [21], employed a bunch of classifiers including support vector machines (SVMs) for crop identification in multiple crop areas of Morocco. They have classified the maize from multiple crops including sugarcane, rice, and cereals with other land use classes. Moorthi et al. 2011 [22], has done a comparative study on Indian satellite data i.e. LISS-III and Advanced Wide Field Sensor (AWiFS) onboard on Resourcesat-1 between traditional (Maximum Likelihood Classifier, MLC) and advanced ML algorithm (SVMs) with an intention to classify the crops from other land use classes in Indian state of Rajasthan. On behalf of their experiments, they have suggested that SVMs with the polynomial kernel can be a better option than linear kernel followed by MLC for crop identification. Whereas, Dimove et al. 2017 [23], used naive Bayesian classifier on multi-temporal RS data to identify the current croplands including the maize crop area. They have reported low Kappa Index Analysis (KIA=0.49) while classifying the data into two classes i.e., crops and others. A good number of studies (Sharma et al. 2016, Sharma et al. 2018, Kumar et al. 2018) reported that SVMs with the polynomial kernel is a better choice for improving both overall accuracy and time complexity [10,12-13]. On the other hand, Guo et al. 2013 [19], used RGB color images with the Classification and Regression Trees (CART) decision tree for wheat segmentation with other ML algorithms. They used spectral signatures for training the classifier by exploiting the different color spaces from the images. Peña et al. 2013 [24], has done multistage experiments using multispectral RS imagery in order to differentiate maize crop from weeds. Initially, both spatial and spectral characteristics have been taken into consideration to generate the superpixels to perform image segmentation for detecting the crop rows. Then segmented imagery was used as input for differentiating the maize crop rows from the weeds.

In another work by Peña et al. 2015 [25], a drone was flown at different altitudes for identification of maize crop using the ML technique. It was achieved with the highest classification accuracy (90%) using CART decision tree techniques on the images captured over the height of 40 meters with a pixel size of 15 millimeters (mm). SVMs have also been used with drone RGB images by Perez-Ortiz et al. [26] in order to segregate maize crop, sunflower, and weeds. In a maize crop-specific study, Goswami et al. 2019 [1], segregate the maize crops from other land use classes including the border area and weed in NER India. They have also reported the potential of SVMs and ANN for analyzing the health of crop using popular ML techniques including SVMs and ANN from drone images. They have reported that SVMs can be used effectively in comparison with ANN for maize crop identification and stress detection. In addition, few important vegetation indices such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Red Edge (NDRE), Plant Senescence Reflectance Index (PSRE), Excessive Green (ExG) etc. have been utilized effectively with ML techniques in order to classify a single crop in multiple crop areas [27-28].

II. Motivation

In the NER of India, it is very challenging to segregate a specific crop from other land use classes. It becomes more challenging in the identification of spectrally similar crops where land patches are so small. It demands comparatively very high-resolution images from a drone and other aerial platforms as moderate resolution satellite data cannot be used because of limitation in pixel size. A camera mounted on a drone can be used for acquiring ultra-spatial resolution images, but challenges still remain as conventional RS classification approaches fail to classify drone images for identification of maize crops from other crops. This study focuses on the usage of high-resolution drone imagery for crop identification using ML approaches to encounter the problem.

III. Objectives

The main objectives of this paper are –

1. Identification of the maize crop from other land use classes including spectrally similar vegetations.
2. Assessment of kernel parameters in improving the performance of SVMs in comparison with MLP and MLC based on predictive accuracy and time complexity.

IV. Study Area, Drone, and Data

A small farming land of Darrang district of NER, Assam, India has been selected for this study. The study area mainly comprised of maize crop and other crops including open and grasslands. Darrang is situated in the central part of Assam on the north bank of the river Brahmaputra having a total area of 142051 hectares of which 73619 hectares is net sown area. The major crops in Darrang are maize, rice, wheat, jute, rape, mustard, pulses, sesame, linseed, sugarcane with vegetables and tea gardens. The map of study area can be found in Figure (Fig. 1.).

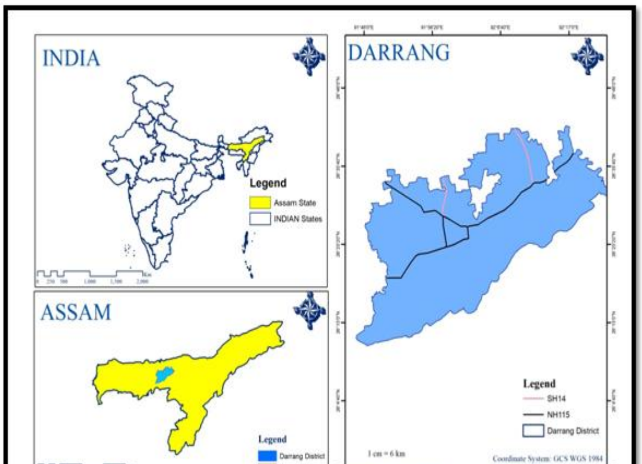

Fig. 1. Map of Study Area (Darrnag, Assam, India)

A. Details of drone used in the investigation

Usages of drones have gained momentum in the field of agriculture as they provide ultra-spatial resolution images. In this study, a lightweight hexacopter Da-Jiang Innovations (DJI) Matrix 600 was employed for the field survey [Fig. 2. (a)]. This model of the drone can fly 45-50 minutes continuously within a radius of 5 km range.

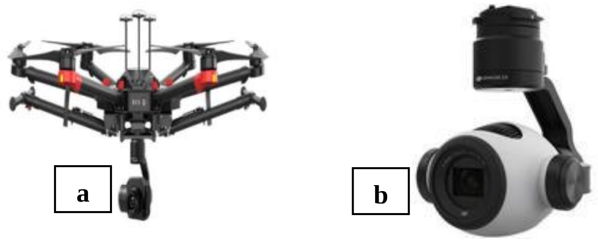

Fig. 2. Drone Model of DJI Thermal Matrice 600 (a) and RGB Camera (b)

A DJI ZENMUSE X3 12.4 Megapixel RGB camera having the 20mm optics and 94-degree diagonal Field of View (FOV) was used in order to collect the data from the field [Fig. 2. (b)]. In drone, the Iphone Operating System (IOS) based DJI flight planner application was used for automatic flight planning. The Geo-location was taken for the accuracy of the onboard Global Positioning System (GPS) [29].

B. Data acquired from drone

The drone image was acquired from a farming land of Darrang comprised of multiple crops other than maize i.e. sugarcane, beans, trees, grass, and open lands [Fig. 3. (a)]. The image was acquired during the month of February 2019 when winter maize crop on its peak [Fig. 3. (b)].

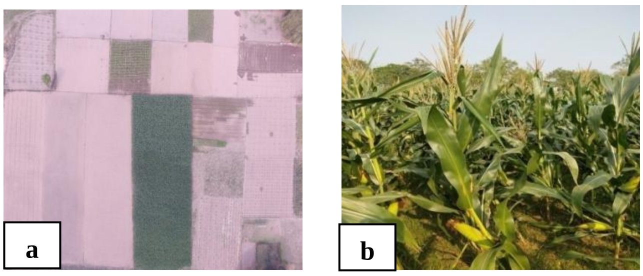

Fig. 3. Input Drone Image (a) and Standing Maize Crop in the Field (b)

The training data were randomly collected from the input image based on ground truth (GT). For testing purpose, GT was used which were collected during a field visit in order to validate the classifiers predictive accuracy. The detail information about the train and test samples are described in the table [TABLE I].

TABLE I. LULC CLASSES AND THIER TRAIN AND TEST SAMPLES

Sl. No.	Class Name	Train Samples	Test Samples
1	Grass	223	210
2	Maize Crop	310	311
3	Beans	451	774
4	Sugarcane	532	603
5	Open Land 1	290	578
6	Open Land 2	356	454
7	Trees	634	623
Total		2796	3553

V. CLASSIFIERS

To identify the maize from multiple crop areas traditional parametric classifier i.e. MLC and advanced non-parametric ML classifiers i.e., MLP and SVMs with its four kernel parameters (linear, polynomial, radial basis function, RBF and sigmoid) were taken in the consideration.

A. Maximum Likelihood Classifier

MLC uses probability function to classify a novel instance. It makes an assumption that the statistics for each output class in each band are normally distributed, therefore it calculates the possibility a given data point belongs to a definite class. It computes the subsequent discriminant functions for each data point in the image. The mathematical equation for MLC is given below [34].

$$g_i(x) = \ln p(w_i) - 1/2 \ln |\sum_i| - 1/2\ (x-m_i)^T \sum_i^{-1} (x-m_i) \quad (1)$$

Where: i is the i^{th} class, x is the n-dimension of dataset, $p(\omega_i)$ is the probability that a class occurs in the image and is assumed the same for all classes, $|\Sigma_i|$ is the determinant of the covariance matrix of the data in a class, Σ_i^{-1} is the inverse of the covariance matrix of a class, m_i is the mean region of interest of a class [30, 35].

B. Support Vector Machines

SVMs use the principle of hyperplane to classify the two class data. However, it encounters the difficulties to classify the multiple class data and requires lots of computational resources. The kernel function is being used with SVMs in order to classify the multiple class data and reducing the time complexity. Linear, Polynomial, RBF, and Sigmoid are the widely used kernel parameters that have register their presence by achieving the higher predictive accuracy with SVMs on many benchmark studies [1, 9, 12-13, 31]. The mathematical equations of all four kernels are given below.

Linear: $K(x_i,x_j) = x_i^T x_j$ (2)

Polynomial: $K(x_i,x_j)= (g\ x_i^T x_j + r)d,\ g > 0$ (3)

RBF: $K(x_i,x_j)= \exp(-g||x_i - x_j||^2),\ g > 0$ (4)

Sigmoid: $K(x_i,x_j)= \tanh\ (g x_i^T x_j +r)$ (5)

C. Multi Layer Perceptron

MLPs belongs to the Feed Forward family of Neural Networks. The simplest type of MLP consists of an input, a hidden and an output layer. Each node in an MLP is a neuron that can be activated by any of a family of nonlinear activation functions like Sigmoid, Tan*h*, ReLU, etc. In the context of classification, the purpose of an MLP is to act as a universal function approximator that can generate an approximation for any kind of function - this is a regression output with classification being a subcategory where the said output is categorical or nominal. In essence, an MLP filters the input data to retain only the minimal distinguishable features that can identify or classify the input. Back-propagation is used to minimize the error or distance between the actual and predicted classes after each data item is consumed by the network - this is how the MLP is said to learn. If the MLP consists of several hidden layers, then it is said to perform deep learning as each layer refines the information gathered from the output to abstract what category it belongs to [32-33]. The activation of neurons can be described as an input vector $x \in R^n$ by the following equation

$$a_\theta(x) = g(\theta^T x) \quad (6)$$

Where θ = vector of n weights
g = an nonlinear activation function

The activation of unit k in some input layer m given its n inputs data ($m-1$, previous layer output) can be described using the below equation

$$a_k{}^m = g(\Theta_{k0}{}^{m-1} a_0{}^{m-1} + \Theta_{k1}{}^{m-1} a_1{}^{m-1} + \dots + \Theta_{kn}{}^{m-1} a_n{}^{m-1}) \quad (7)$$

VI. RESULTS

The study area comprises a total seven heterogeneous land use classes. The major aim was to identify the maize crop from the drone imagery. Three popular supervised classifiers have been trained with a set of training samples. The MLC was initialized with a probability function of 0.95 whereas MLP was modeled with 3 numbers of hidden layers via a hyperbolic activation function. Since in the initial testing phase SVMs achieved comparatively higher performance it was decided to assess the effectiveness of the four kernel parameters in order to improve classification performance. KIA, Overall Accuracy (OA) and Receiver Operating Characteristic (ROC) have been utilized for performance assessment of the investigation. All the classifiers have been assessed based on the independently generated train and test samples in order to avoid the bias in the performance. The experiment was carried out on HP-Z210 workstation having the Intel XEON-31245 processor that can perform the operations with 3.30 gigahertz (GHz) clock cycles. The four physical cores of the workstation can be utilized in parallel processing mode and able to execute the intricate processing tasks with the support of its 16 gigabytes primary memory.

It was observed that MLC has shown poor classification performance as compared to the other classifiers. It achieved OA=66.76% with KIA=0.62, and ROC=0.92 see table [TABLE II]. It failed to identify maize crops and the maize crop class accuracy was 53.21% only. MLC is a parametric classifier which is based on the assumption that data distribution should be normal. However, drone images are characterized by ultra high-spatial resolution which gives high variance in the data. This could be the major issue with the MLC for not achieving high performance even though computational expenses were far better than all other classifiers.

On the other hand, MLP has shown comparable performance with SVMs. It achieved OA=78.24% with KIA=0.76 and ROC=0.91 [TABLE II]. It classified maize crop with 71.06% class accuracy. However, some misclassifications have been observed in the identification of bean, sugarcane including other land use classes. The major limitation of MLP was higher computational expenses while building the training model (time=247.45 sec). In the MLP, selection of an optimal number of hidden layers is also an issue, as a larger number of hidden layers encounters higher computational expenses. Another issue with the MLP is that it cannot achieve satisfactory results if either training data are not properly defined or the size of training data is less. It was observed that SVMs with the polynomial kernel (SVM^P) outperformed the all classifiers with OA=82.29%, KIA=0.78 and ROC=0.94 [TABLE II].

TABLE II. ACCURACY OF THE CLASSIFIERS

Classifiers	Evaluation Parameters			
	OA %	*KIA*	*ROC*	*Time (s)*
MLC	66.76	0.62	0.92	0.20
MLP	78.24	0.76	0.91	247.45
SVM^P	82.29	0.78	0.94	05.26
SVM^S	73.37	0.68	0.88	13.92
SVM^L	70.33	0.66	0.91	15.98
SVM^{RBF}	77.39	0.74	0.90	28.34

Classified maps of all classifiers are depicted in the figure [Fig. 4.]. The maize crop classification accuracy (89.46%) was comparatively higher than the OA of SVMs with the polynomial kernel. It was also observed that there is very minimal miss classification among the other land use classes [Fig. 4.].

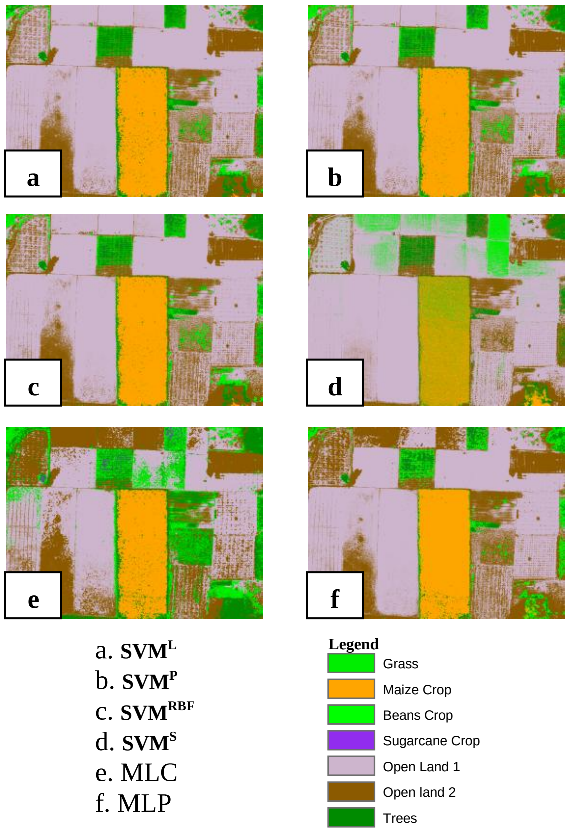

Fig. 4. Classified Output Images of all classifiers

The grassland class classification accuracy was 81.22% followed by tress=72.41%, sugarcane=59.65% of SVM^P.

However, other crops like beans and sugarcane were partially identified as they are scattered within the other land use classes. This is basically due to the lack of spectral information in the dataset. However, the selection of kernel parameter is also crucial in improving the classification performance of SVMs. The investigation has shown that SVM^P can achieve higher performance as compared to the other kernels. In comparison of SVM^P, SVMs with RBF kernel (SVM^{RBF}) also achieved the satisfactory performance (OA=77.39%, KIA=0.74, ROC=0.90) followed by SVMs with sigmoid kernel (SVM^S) (OA=73.37%, KIA=0.68, ROC=0.88) and SVMs with Linear kernel (SVM^L) (OA=70.33%, KIA=0.66, ROC=0.91) [TABLE II]. The major advantage observed for SVM^p is that it not only results higher accuracy, it also reduces computational expenses when used with an appropriate degree. In addition, it was found that SVM^P was not affected by overfitting as degree 3 fitted the curve over the training data in an effective manner.

VII. CONCLUSION

The major emphasis given in the investigation was to identify the maize crop from drone images. Results obtained using SVMs classifier were quite encouraging. SVM^p kernel correctly identified the maize crop with a certain accuracy level. The training dataset was defined based on the spatial characteristics of the drone images. However, minor misclassification could be avoided using spatial morphological characteristics of the training dataset. The study has shown that SVM classifier has good potential in the identification of crops from high-resolution RGB drone images. However, SVMs based classification approaches need to be tuned to work with multispectral drone images. On the other hand, deep learning based CNN (Convolution Neural Network) with an optimal set of features can be also explored in order to reduce the misclassification rate and time complexity of the model.

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