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MACHINE LEARNING IN CROP CLASSIFICATION OF TEMPORAL MULTISPECTRAL SATELLITE IMAGE

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MACHINE LEARNING IN CROP CLASSIFICATION OF TEMPORAL
MULTISPECTRAL SATELLITE IMAGE

A Writing Project

Presented to

The Faculty of the Department of Computer Science

San José State University

In Partial Fulfillment

of the Requirements for the Degree

Master of Science

by

Ravali Koppaka

May 2019

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The Designated Writing Project Committee Approves the Project Titled

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MULTISPECTRAL SATELLITE IMAGE

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ABSTRACT

MACHINE LEARNING IN CROP CLASSIFICATION OF TEMPORAL MULTISPECTRAL SATELLITE IMAGE

by Ravali Koppaka

Recently, there has been a remarkable growth in Artificial Intelligence (AI) with the development of efficient AI models and high-power computational resources for processing complex datasets. There has been a growing number of applications of machine learning in satellite remote sensing image data processing. In this work, machine learning methods were applied for crop classification of temporal multi-spectral satellite image to achieve better prediction of crop-wise area statistics. In India, agriculture has a huge impact on the national economy and most of the critical decisions are dependent on agricultural statistics. Sentinel-2 satellite image data for the Guntur district region of Andhra Pradesh, India has been used as the study area. The main reason for selecting this region is the diversity of agricultural crops and the availability of ground truth. As a baseline, the performance of machine learning models like Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), and K-Nearest Neighbor (KNN) on crop classification was evaluated on 2016 single time multi-spectral satellite image. SVM performed well with an F1 score of 0.94. Further, the performance of SVM, RF, 1D and 2D Convolutional Neural Network (CNN), Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) and RNN with Gated Recurrent Unit (GRU) on 2018 Kharif season temporal multi-spectral satellite image has been evaluated for estimation of crop areas. The results show that SVM has the best F1 score of 0.99 and achieved a 95.9% agreement with the ground surveyed crop areas.

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LIST OF ABBREVIATIONS

AI – Artificial Intelligence
APSAC – Andhra Pradesh Space Application Center
CNN – Convolutional Neural Network
CSV – Comma Separated Value
DBN – Deep Belief Networks
DT – Decision Tree
FCC – False Composite Color
GIS – Geographical Information Systems
GPS – Geographical Positioning System
GRU – Gated Recurrent Unit
KNN – K-Nearest Neighbor
LSTM – Long Short-Term Memory
MLC – Maximum Likelihood Classifier
MSI – Multi-Spectral Instrument
NDVI – Normalized Difference Vegetation Index
RF – Random Forest
RNN – Recurrent Neural Network
SAE – Stacked Auto-Encoder
SVM – Support Vector Machine
USGS – United States Geological Survey
UTM – Universal Transverse Mercator
WGS – World Geodetic System

Introduction

In India, one of the main sources of national income is agriculture. The Indian population largely depends on agriculture. Timely and reliable agricultural crop-wise area statistics are important for making decisions on various agro-economic policies [1], [2], [3]. These statistics help in forecasting crop-wise production, in marketing, in decision making for exports, imports and covering the insurance for crops during drought, and natural calamities.

In India traditionally, during each crop season, a village revenue officer (called as Patwari) does the field inspection and records the crop-wise area. This information is aggregated at different levels from villages to districts, from districts to states and from states to country [4]. These traditional techniques are prone to human errors and limit the scope of making crucial decisions in agro-economics.

For the past few decades, satellite remote sensing images have been used for estimation of the crop-wise area using image processing classification techniques like maximum likelihood classification (MLC) [4], [5]. MLC classifier is a parametric model which assumes normal distribution thereby limiting the discrimination of crops based on the spectral characteristics. Non-parametric models do not make any underlying assumptions, unlike parametric models which give the ability to seek the best fit on training data and generalize well for unseen data. In this work, to overcome the limitation of MLC non-parametric supervised machine learning techniques like Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) have been explored. Also, crop phenology gives growth stages of the crop which is one of the important factors for crop discrimination.

Hence, temporal satellite images for the selected region are collected and methods like SVM, RF, and deep learning have been explored.

Deep learning, a subset of machine learning, learns incrementally through its hidden layers. Deep learning techniques, with its deep neural network and non-linearity activation function, generalize from the data which makes a well-pertained model reusable on new unseen data. Non-linearity of the neural network captures the complex structure of the data which otherwise requires a domain expert or involves feature engineering. Deep learning methods like Convolutional Neural Network (CNN) are very efficient in feature extraction from images. The interleaving of convolutional and pooling layers of CNN efficiently extract mid-level and high-level features from raw images [6]. Recurrent Neural Network (RNN) has been successful in analyzing time series or sequential data. For crop classification from the temporal, multi-spectral satellite image, deep learning methods were designed and developed using CNN and RNN [7].

Related Study

Agriculture Annual Report 2017-2018 of India describes that though the earliest records of crop production statistics are mentioned in Kantilla's Arthashastra during 2nd century BCE and 3rd century CE, systematic agricultural statistics started in 1884 with wheat [8]. In traditional methods, the crop area numbers are reported by village revenue office known as Patwari. These values are successively aggregated at district-level and state-level which are then finally submitted to the Directorate of Economics and Statistics in the Ministry of Agriculture for issuing all India estimates.

The results from the traditional methods are generally time taking and are not efficient.

Carfagna and Keita states that availability of Geographical Positioning System (GPS) enabled mobiles and computer tablets allows to process data from anywhere which emphasizes to incorporate modern techniques for efficient crop-wise statistics [9]. In [10] Sharman discusses about how the Directorate General for Agriculture of European Community is using different sensors remote sensing image data for important crop production estimates. Remote sensing, Geographical Information Systems (GIS) began to make a real impact in the 1980s. Remote Sensing technology is being used operationally by many countries. Department of Agriculture of US has been using remote sensing along with models which calculate the moisture content in soil and the yield from a crop for estimating agricultural production globally. In India, crop classification has been operationally used from the launch of first India Remote Sensing Satellites (IRS-1A) in 1988.

Yang et.al (2011) discusses about using multispectral image for crop classification. Commonly, image processing-based classification techniques are used for crops identification and discrimination of different land covers from multi-spectral remote sensing data. In a multispectral image, a crop has a unique spectral signature which is the basic criteria for crop discrimination [11]. Prasad et al. (2015) provided a survey of techniques that may be used for remote sensing image data classification. Some of the common algorithms for supervised classification are minimum-distance-to-means, parallelepiped, and MLC while for unsupervised classification ISODATA and K-Means are commonly applicable. In [12] Hooda et al. conducted studies on utilisation of IRS remote sensing image data classification techniques, specific to

wheat area estimation and production in the state of Haryana, India. This study reported that the wheat crop area and production at district-level estimates are within 5 percent of official Indian estimates. There were also much poor results when the changes were difficult to predict due to subjectivity in pixel-based classification without much ground data [12]. With multispectral satellite image, the limitation for crop identification is the plant reflectance is correlated for different crops and for same crop it shows parcel-to-parcel variability of the plant reflectance [11].

Zang et al. surveyed on deep learning techniques for remote sensing image data classification. The survey introduced several deep learning models like CNNs, Stacked Auto-Encoder (SAE) and Deep Belief Networks (DBN) that were used for remote sensing data classification [6]. Deep learning models are based on remote sensing multispectral features, spatial features and joint spectral & spatial features for both unsupervised and supervised classification [13]. SVMs are nonparametric statistical approaches for supervised classification and regression problems. A survey of recently developed SVM for remote sensing image classification is explained in [14]. This survey focused on SVM based classification, including active SVMs and composite SVMs for remote sensing image data classification.

Study Area and Data

Krishna river delta area located between upper left corner latitude $16^{\circ} 25'$, longitude $80^{\circ} 36'$ and lower bottom right corner latitude $16^{\circ} 15'$ and longitude $80^{\circ} 47'$ in Guntur district, Andhra Pradesh state, India is selected. Fig 1. below shows the study area selected for this work. The main reasons for selected this region are (1) multiple crops are grown in Indian Kharif crop season (June-November) and (2)

support of Andhra Pradesh Space Application Centre (APSAC) for ground truth required for preparation of training data.

Fig 1. Study Area

Open source Sentinel-2 remote sensing satellite image data acquired on October 23, 2016, and on June 6, August 4, October 8, 2018, over the study area has been downloaded from United States Geological Survey (USGS) earth explorer agency. European Space Agency has developed Sentinel-2 which is a constellation of two earth observation satellites Sentinel-2A, launched on June 23, 2015, and Sentinel-2B launched on March 7, 2017. Sentinel-2 carry Multi-Spectral Instrument (MSI) acquiring image data in 13 spectral bands along the visible and infrared region of the electromagnetic spectrum, with a ground swath of 290 km [15]. Each satellite has a 10-day orbit (duration to complete one full orbit around Earth). Using both Sentinel-2A and Sentinel-2B satellites, more frequent time series data with a 5-day period can be collected. The spectral and spatial resolution specifications of the bands used in this work are given in Table I.

TABLE I. SENTINEL -2 SENSOR SPECTRAL BANDS SPECIFICATIONS

Sentinel-2 Bands	Central Wavelength (μm)	Spatial Resolution (m)	Bandwidth (nm)
Band 2 – Blue	0.490	10	98
Band 3 – Green	0.560	10	45
Band 4 – Red	0.665	10	38
Band 8 – NIR	0.842	10	115

Sentinel -2 remote sensing images are available in Level-1C and Level-2A processing levels. Level-1C product images contain Top-Of-Atmosphere reflected data. Level-2A products are Bottom-Of-Atmosphere, terrain, and cirrus corrected reflected images. Sen2Cor is a processor for Sentinel-2 for the generation of Level-2A products from Level -1C) [16]. Sentinel-2 remote sensing images are orthorectified in World Geodetic System (WGS) WGS84 datum and Universal Transverse Mercator (UTM) map projection earth coordinate system, which ensures the geographical positional co-registration of time series images of any specific region of the earth.

Commonly remote sensing images are displayed in False Color Composite (FCC) mode. In FCC display mode near infrared band image data is sent to the red gun, red band data is sent to the green gun, green band image data is sent to the blue gun. In FCC display mode vegetation is seen in different shades of red color and the human eye can distinguish more shades of red [17]. Fig. 2 shows the study area in FCC mode.

Fig. 2 Study area displayed in FCC mode

Multispectral Remote Sensing Data Spectral Characteristics

Each material has a unique spectral signature which becomes the basic criterion for material identification. The graph below in Fig. 3 depicts the typical reflectance characteristics of water, vegetation, and soil. The typical curves of water, vegetation and soils are close in the visible region and quite different in the infrared spectrum. The basic information for developing classification models is discriminative reflectance characteristics of materials at different wavelengths [17].

The spectral reflectance characteristics of Sentinel -2 image data for different crops in the study area are presented in Fig. 4. In the visible region, the spectral reflectance values of different crops are close but in the infrared region, crops are discriminable.

Fig. 3 Water, vegetation and soil typical reflectance characteristics at different wavelengths

Fig. 4 Characteristics of different crops in different spectral bands

Dataset Preparation

The temporal satellite images collected for 2018 on June 6, August 4 and October 8 are shown in Fig 5. Temporal data captures the crop phenology which is an important factor for crop discrimination. As the crop grows, more energy is reflected in the infrared band which can be observed in satellite image for October 23. In FCC mode, infrared band values are sent to the red gun of the display image.

Fig. 5 Temporal Satellite Images

The pipeline for creating the dataset that is compatible with machine learning methods from temporal multi-spectral satellite image is shown in Fig. 6.

Image to Comma Separated Value (CSV)

The input satellite image is in raster format which is read pixel by pixel and written in CSV format with each pixel as a row and the band values for each pixel as a column.

Calculate Feature

Normalized Difference Vegetation Index (NDVI) is a quantitative measure of vegetation which is calculated using the red band and Near-Infrared (NIR) band [18].

$$NDVI = (NIR - Red) / (NIR + Red)$$

NDVI values range from -1 to +1 and values closer to +1 indicate dense vegetation while values close to -1 indicate water.

Fig. 6 Dataset preparation pipeline from temporal multi-spectral satellite images to a temporal dataset in CSV format

Normalize

Normalization of data is commonly done for machine learning methods to avoid the dominance of individual features. For this data, standardization using Gaussian distribution with mean zero and variance as one was used for normalizing the band values.

Stack

To create time series data, the CSV data created from each image is column stacked after concatenating NDVI and normalized data. So, each row, which represents a pixel in the image, has band values at time t1 followed by band values at time t2 and so on.

Machine Learning Methods

Non-parametric machine learning methods are considered better for crop classification than parametric methods like MLC because they do not assume about the data. They learn from the training data and try to find the best hypothesis which is used to predict new data.

Generally, there are no fixed, best machine learning method. For a given data, the best machine learning method is found from the experimental results [19]. For crop classification of the single time satellite image, DT, RF, SVM, and KNN supervised machine learning methods have been explored. Whereas for time series or temporal data SVM, RF, deep learning methods like 1D CNN, 2D CNN, RNN with Long Short-Term Memory (LSTM) and RNN with Gated Recurrent Unit (GRU) have been explored.

Decision Tree

A decision tree is one of the simplest and intuitive machine learning method. It is a tree data structure which splits the labeled training data at each node. Nodes of the tree are features which are chosen based on information gain. Features with the highest information gain are closer to the root. One major drawback with a decision tree is it is easily prone to overfitting. Entropy and information gain of features are defined as follows [20]

$$\text{Entropy: } E(T) = \sum_{i=1}^C -p_i \log p_i$$

$$E(T, X) = \sum_{c \in X} P(c) E(c) ; c \text{ is data column}$$

$$\text{Information Gain: } \text{Gain}(T, X) = E(T) - E(T, X)$$

where p , P is probability and T , X are attributes

Random Forest

Random forest is a generalized method of the decision tree. It overcomes the major drawback of the decision tree by using the concept of bagging. In bagging, multiple decision trees are constructed using a subset of training data and a subset of features for each tree and output is determined by the either considering majority vote or calculating the average of all trees. Random forest is generally faster in training and but slow in predicting [21].

Support Vector Machine

SVM is a kernel based supervised machine learning method. It explores the geometrical properties of the data and aims at finding the optimal hyperplane that linearly separates the data into two classes with a larger margin. A hyperplane is defined as an $n - 1$ dimensional subspace which separates the n -dimensional space

into two disconnected spaces. A margin is defined as the minimum distance between the hyperplane and training data point. Kernel is the most important and tricky part of SVM. It maps data to higher dimensions when the data is not linearly separable. Compared to other methods SVM is less sensitive to the curse of dimensionality and tries to achieve structural risk mitigation while others try to achieve empirical risk mitigations [22].

Hyperplane equation: $w \cdot x_i + b \geq 1$

where x_i is the data point labelled as class '1' and

'w', 'b' is determined during training for an optimal hyperplane.

K Nearest Neighbor

KNN is a neighborhood-based classifier where a data point is classified based on the classification of 'k' closest points. KNN does not require training and is not prone to overfitting. They are generally slow when considering large training datasets and are very sensitive to higher dimensional data [19].

Convolutional Neural Network

CNN is a deep learning method with convolutional, pooling and fully connected layers. Convolutional and pooling layers do the feature extraction while fully connected layers do the classification. CNN is very efficient in extracting mid-level and high-level features especially with image data. They are generally successful in capturing spatial and temporal characteristics in data [23].

The kernel is the main component of the convolutional layer which captures the features in the input image. 1D CNN has a one-dimensional kernel that is generally good with time series while 2D CNN efficiently captures spatial

features. Fig. 7 and Fig. 8 below respectively gives the architecture of 1D CNN and 2D CNN used in this work.

Fig.7 1D CNN Architecture

Fig.8 2D CNN Architecture

Recurrent Neural Network

RNN is also a deep learning method that makes use of sequential information in input data. Most of the traditional neural networks do not use previously generated output. This major short come of traditional neural network is addressed by RNN [24]. So, for time series or sequential data classification and prediction, generally, RNN perform better. During training, to avoid vanishing and exploding gradient problem long-term dependencies need to be captured. LSTM and GRU units track long-term dependencies to mitigate the vanishing and exploding gradient problem [25]. Fig.9 gives the RNN architecture used in this work.

Fig. 9 RNN LSTM and GRU Architecture

Experimental Results

Development Environment and libraries

Orfeo Toolbox (OTB) is an open source state-of-art library for remote sensing image processing. It can process terabytes of high resolution optical and multispectral images. The library has a collection of image processing and machine learning algorithms written in C++ language which are available as wrapper methods in Python [26], [27], [28]. Classification by SVM, RF, DT and KNN on single-time multi-spectral satellite image was experimented using OTB library.

Quantum Geographic Information System (QGIS) software is an open-source desktop application for visualizing, analyzing and editing geospatial data. It has support for raster and vectors layers. Vector layer was used to view and create shape files of training data from the ground truth. Raster layer was used for displaying input satellite images and classified color coded output images [29].

Python is the most commonly used scripting language for machine learning due to the rich collection of libraries. Dataset creation, training, and evaluation of

models for temporal multispectral satellite images was done using python. Python libraries pandas and numpy was used for dataset creation. Machine learning libraries scikit-learn and Keras with the Tensorflow framework was used for constructing and training models [30], [31], [32]. For hyperparameter optimization of models, GridSearchCv of scikit-learn and hyperas [33] was used.

All the models were trained and experimented on a 12GB RAM, Intel® Core™ i5-7200U CPU @ 2.50GHz 2.71 GHz, a dual-core CPU. For hyperparameter optimization for deep learning models using hyperas a dedicated GPU machine of 29GB system memory, Intel® Xeon® CPU ES-2623 v4 @ 2.60GHz, an 8core CPU and Quadro M4000 GPU was rented from paperspace [34].

Evaluation metric

Confusion matrix with precision, recall and F1 scores was used for evaluating the machine learning methods. A confusion matrix is a table which gives a visual performance of the model on the test data. Precision gives the measure of correctly predicted class values over the total predicted class values. Recall is a ratio of correctly predicted class values to the actual class values. F1 score is calculated as a harmonic mean of precision and recall [35]. For multiclass with imbalanced data, the F1 score is the best metric for performance comparison of methods [36].

$$\text{precision} = TP / (TP + FP); \text{ TP - True Positive, FP - False Positive}$$

$$\text{recall} = TP / (TP + FN); \text{ FN - False Negative}$$

$$\text{F1-Score} = (1/\text{precision}) + (1/\text{recall})$$

Experiments with single time satellite image

SVM, RF, DT and KNN models was trained over 2016 satellite image using OTB library. From the experimental results, SVM with linear kernel has the best classification with an F1 score of 0.94. Though KNN with k=5 also had an F1 score of 0.94, major crops like paddy, sugarcane, and turmeric were better classified by SVM. Moreover, as the dimension of the data increases, KNN suffers from the curse of dimensionality while SVM is less sensitive to high dimensional data. Tables II, III below gives the confusion matrix of SVM and KNN respectively. The graph for the comparison of mean F1 scores for all models is shown in Fig 10.

TABLE II. CONFUSION MATRIX FOR SVM CLASSIFICATION

Class Label	Code	1	2	3	4	5	6	7
Settlement/Dry sand	1	2344	0	0	0	35	8	0
Water	2	0	2169	0	0	0	0	0
Paddy	3	0	0	6150	0	0	33	0
Sugarcane	4	0	0	10	799	0	0	0
Turmeric	5	0	0	0	9	245	0	0
Plantation	6	0	0	227	88	0	639	0
Wet Fallow/Wet area	7	0	0	0	0	0	0	793

TABLE II. CONTINUED: CONFUSION MATRIX FOR SVM CLASSIFICATION

Class Label	Precision	Recall	F1 Score
Settlement/Dry sand	0.98	1	0.99
Water	1	1	1

Paddy	0.99	0.96	0.97
Sugarcane	0.98	0.89	0.93
Turmeric	0.96	0.875	0.92
Plantation	0.66	0.93	0.77
Wet Fallow/Wet area	1	1	1
$\mu \pm \sigma$	0.94$\pm$0.11	0.95$\pm$0.05	0.94$\pm$0.07

TABLE III. CONFUSION MATRIX FOR KNN (K=5) CLASSIFICATION

Class Label	Code	1	2	3	4	5	6	7
Settlement/Dry sand	1	2376	0	0	0	5	6	0
Water	2	0	2169	0	0	0	0	0
Paddy	3	0	0	6091	3	0	89	0
Sugarcane	4	0	0	0	752	0	57	0
Turmeric	5	0	0	0	58	196	0	0
Plantation	6	31	0	80	11	0	832	0
Wet Fallow/Wet area	7	0	0	0	0	0	0	793

TABLE III. CONTINUED: CONFUSION MATRIX FOR KNN (K=5) CLASSIFICATION

Class Label	Precision	Recall	F1 Score
Settlement/Dry sand	0.99	0.98	0.98
Water	1	1	1
Paddy	0.98	0.98	0.98
Sugarcane	0.93	0.91	0.92
Turmeric	0.77	0.97	0.86

Plantation	0.87	0.84	0.85
Wet Fallow/Wet area	1	1	1
$\mu \pm \sigma$	0.93 ± 0.08	0.95 ± 0.05	0.94 ± 0.06

Fig. 10 Mean F1 scores for classification of 2016 satellite image

Experiments with temporal satellite image

Temporal multi-spectral satellite images collected on June 6, August 4, October 8 for 2018 was used to train SVM, RF, 1D CNN, 2D CNN, RNN-LSTM, and RNN-GRU models. The size of the input satellite image is 5110 * 3163 with 16 million-pixel values in red, green, blue and near-infrared bands. Of these,

78969 pixels were labeled using ground truth. Models were trained using 70% of the labeled data and evaluated with the remaining 30% data. The training samples collected for crop class is shown in Table IV.

TABLE IV. CROP-WISE TRAINING SAMPLES

Crop Type	Training Samples
Paddy	34302
Sugarcane	1757
Banana	101
Lemon	1548
Jasmine	591
Turmeric	131

Experimental results show that SVM with radial basis function (RBF) kernel, $\gamma = 1$ and $C = 10$ has the best classification result with an F1 score of 0.994. RF with $n_estimators = 1000$, $max_depth = 120$ has also classified crops well with an F1 score of 0.987. Compared to RF, SVM has the best classification results for all crops including Banana and Turmeric which has less training samples.

Moreover, RF with 1000 estimators takes a longer time for training and prediction. Fig 11. shows the color-coded classification output of the SVM model.

Among the deep learning models, 1D-CNN one layer of convolution with $filters = 128$ and $kernel\ size = 2$ had an F1 score of 0.843. RNN-LSTM one layer of LSTM with $units = 64$ had a similar F1 score of 0.835. Comparison of mean F1 scores of all models is shown in Fig. 12.

Fig. 11 Classification output of SVM

Fig 12. Mean F1 score for classification of 2018 satellite image

For further evaluation of models, stratified 10-fold cross validation was used. In stratified 10-fold validation, the entire training data is partitioned into 10 folds with each fold representing the whole data. The model is evaluated by iteratively training on 9 folds and testing with the remaining 10th fold.

Experiments with 10-fold validation show that SVM and RF have consistent results with 70, 30 train test split validation. Confusion matrix of SVM and RF evaluation with 10-fold are shown in Table V, Table VI. Comparison of F1-scores of models with 10-fold validation is shown in Fig 13.

Fig 13. F1 score of models with 10-fold validation

TABLE V. CONFUSION MATRIX FOR SVM 2018 CROP CLASSIFICATION

Class Label	Code	1	2	3	4	5
Paddy	1	34301	0	1	0	0
Sugarcane	2	0	1755	0	1	0
Banana	3	0	0	99	1	0
Lemon	4	0	0	0	1544	0
Jasmine	5	0	0	0	0	591
Turmeric	6	0	0	2	0	0
Built-up/River sand	7	0	0	1	0	0
Water	8	0	0	0	0	0
Plantation	9	0	0	0	1	0
Fallow Land	10	0	0	0	0	0

TABLE V. CONTINUED: CONFUSION MATRIX FOR SVM 2018 CROP CLASSIFICATION

Class Label	Code	6	7	8	9	10
Paddy	1	0	0	0	0	0
Sugarcane	2	0	0	0	1	0
Banana	3	1	0	0	0	0
Lemon	4	0	3	0	1	0
Jasmine	5	0	0	0	0	0
Turmeric	6	128	1	0	0	0
Built-up/River sand	7	0	6910	0	0	0
Water	8	0	0	3632	0	0
Plantation	9	0	0	0	14781	0

Fallow Land	10	0	1	0	0	15213
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TABLE V. CONTINUED: CONFUSION MATRIX FOR SVM 2018 CROP CLASSIFICATION

Class Label	Precision	Recall	F1 score
Paddy	1	1	1
Sugarcane	1	1	1
Banana	0.96	0.98	0.97
Lemon	1	1	1
Jasmine	1	1	1
Turmeric	0.99	0.98	0.98
Built-up/River sand	1	1	1
Water	1	1	1
Plantation	1	1	1
Fallow Land	1	1	1
$\mu \pm \sigma$	0.994$\pm$0.01	0.996$\pm$0.008	0.994$\pm$0.01

TABLE VI. CONFUSION MATRIX FOR RF 2018 CROP CLASSIFICATION

Class Label	Code	1	2	3	4	5
Paddy	1	34301	0	1	0	0
Sugarcane	2	0	1748	0	8	0
Banana	3	6	0	92	2	0
Lemon	4	0	3	0	1540	0
Jasmine	5	3	0	0	3	579
Turmeric	6	5	0	1	0	0

Built-up/River sand	7	0	0	2	1	0
Water	8	0	0	0	0	0
Plantation	9	0	0	0	1	0
Fallow Land	10	0	0	0	0	0

TABLE VI. CONTINUED: CONFUSION MATRIX FOR RF 2018 CROP CLASSIFICATION

Class Label	Code	6	7	8	9	10
Paddy	1	0	0	0	0	0
Sugarcane	2	0	0	0	1	0
Banana	3	1	0	0	0	0
Lemon	4	0	0	0	5	0
Jasmine	5	0	0	0	6	0
Turmeric	6	121	0	0	3	1
Built-up/River sand	7	0	6907	0	0	1
Water	8	0	0	3632	0	0
Plantation	9	0	0	0	14781	0
Fallow Land	10	0	0	0	0	15214

TABLE VI. CONTINUED: CONFUSION MATRIX FOR RF 2018 CROP CLASSIFICATION

Class Label	Precision	Recall	F1 score
Paddy	1	1	1
Sugarcane	1	0.99	1
Banana	0.96	0.91	0.93
Lemon	0.99	0.99	0.99

Jasmine	1	0.98	0.99
Turmeric	0.99	0.92	0.96
Built-up/River sand	1	1	1
Water	1	1	1
Plantation	1	1	1
Fallow Land	1	1	1
$\mu \pm \sigma$	0.994$\pm$0.01	0.978$\pm$0.03	0.987$\pm$0.02

Comparison of crop areas with ground survey

Ground-survey based crop areas for all major crops: paddy, sugarcane, banana, lemon, and turmeric were collected for 2018 with the support of APSAC. These ground-surveyed crop areas were used for comparison of crop area statistics generated from the trained models.

Of all models, SVM has the highest agreement of 95.9% with the ground-based crop areas which is shown in Fig 14. Among all the major crops, Paddy is the main crop cultivated in this study area during the Kharif season. Comparing each crop area with the ground-surveyed area show that all models have estimated paddy area accurately. For paddy, the models have a variation of less than 7% with a ground survey area as shown in Fig. 15. Table VII shows SVM generated crop areas and the ground-survey crop areas while Table VIII gives the calculation of percentage agreement with ground survey areas.

TABLE VII. SVM CROP AREAS AND GROUND SURVEY CROP AREAS

Class	Areas from SVM Model (Acres)	Areas from Ground Survey (Acres)
Paddy	191870	199549
Sugarcane	15624	15155
Banana	10907	10471
Lemon	21123	19644
Turmeric	5828	5945
Total crop area		250764

TABLE VIII. CALCULATION OF PERCENTAGE AGREEMENT WITH GROUND AREAS FOR SVM

Class	(Ground –SVM Model) in Acres	% of variation	Abs (% of Variation)	Weights = Crop area/Total crop area	Weights*Abs (% of variation)
Paddy	7679	3.8	3.8	0.795	3.021
Sugarcane	-469	-3.1	3.1	0.06	0.186
Banana	-439	-4.2	4.2	0.041	0.1722
Lemon	-1470	-7.5	7.5	0.078	0.585
Turmeric	117	2	2	0.02	0.04
Weighted average % variation					4.00042
% Agreement					95.9

Fig. 14 Percentage agreement of crop areas with ground survey

Fig. 15 Percentage variation of paddy crop area with ground survey

To the best of our knowledge, most of the published studies on machine learning for crop classification have considered ideal study areas and evaluation of the models was done based on labelled test data. The study area considered for this work is a heterogeneous crop area with realistic data which makes it challenging and for the first-time crop-wise areas derived from models were compared with ground surveyed crop areas.

Conclusion

Crop-wise area statistics are critical information for Indian agroeconomics. For the past few decades, multispectral remote sensing images and parametric image classification methods like MLC were used for crop area estimates for major crops. The limitation of this method is that it assumes data in normal distribution which may not always be true, leading to failure in accurate crop discrimination. In this work, non-parametric machine learning methods were experimented.

Indian Krishna river delta area where multiple crops are grown in Kharif season has been used as a study area. Sentinel-2 image data acquired on 23, 2016 has been classified using machine learning methods SVM, RF, DT, and KNN. Among these methods, SVM has resulted in a good F1 score of 0.94.

Temporal Sentinel-2 images acquired for 2018 on June 6, August 4 and October 8 has been classified using SVM, RF, 1D-CNN, 2D-CNN, RNN-LSTM, and RNN-GRU. Even with temporal data, SVM has the best F1 score of 0.994 with an improvement of 5.7% over the single time satellite image. Crop-wise areas generated by models was compared with the 2018 ground-survey based crop areas given by APSAC. SVM had the highest agreement of 95.9% with the ground surveyed crop areas.

Hence, generally temporal satellite images improve classification accuracy and SVM performed better than most of the models. In remote sensing applications, getting large training samples is a challenge and generally, deep learning methods require larger training data for better performance. With limited training data, SVM performed the best as they learn from the geometric structure of the data and try to achieve structural risk mitigation instead of empirical risk mitigation. Achieving crop area estimates with 95.9% agreement with ground surveyed areas represents a notable research contribution of this work.

Future Work

Future research may focus on the development of generic training model for temporal satellite images classification that is trained once and can be reused to predict crops for the next year. Towards this, preparing the training data is the major challenge because the data for different years should be collected as the crop plantation time varies with each year.

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