Transfer Learning for Plant-level Crop Classification using Drone-based Hyperspectral Imagery

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***Abstract*—Sensing and imaging technologies are revolutionizing the way crop cultivation is done. Hyperspectral imaging has been increasingly used for crop discrimination, yield estimation, disease detection, etc. However, most of the studies have focused on regional or field-level mapping units. For effective intervention at the farmer level, crop / soil information at sub-field, preferably at the plant level is vital. Further, the crop-specific information has to be obtained in a near-real time for time critical interventions. Traditional method of image classification which requires expert-driven model initiation and ground truth data acquisition is not suitable for time-critical image analysis. A method which can analyse imagery on the go and without human intervention is essential. The distinct spectral fingerprints of objects characterized by hyperspectral imagery prove a basis for automated spectral imaging analysis. A methodological perspective, transfer learning, is a viable approach for effective utilization of spectral knowledge characterized in a previous image analysis task for classifying imagery at a different space and time level. We present a spectral matching based transfer learning method for automated classification of drone based hyperspectral for plant level crop discrimination. The proposed method is applied for the classification of vegetable crops using drone based hyperspectral imagery acquired over, GKVK, Bangalore, India. Results are promising with accuracy varying between 65 to 85% for different cases of imagery and crops combinations.**

***Index Terms*—transfer learning, structural similarity index, normalized spectral similarity score spectral information divergence**

I. Introduction

Agriculture is a crucial factor in the economic development of any country. Precision agriculture, which focuses on farm management with optimized returns, is an active area of research [1]. High-resolution remote sensing has been progressively used as the data for mapping and monitoring of crops at the regional level, with recent emphasis on field-level [2].Hyperspectral imagery has the potential to be a primary data for deriving a host of crop and soil parameters. Crop type is a general parameter which needs to be considered for retrieving various parameters related to crop status. Hyperspectral imagery from a drone-based platform is an appropriate source of spectral data for enabling sub-field or plant level information extraction. Remote sensing imagery, including hyperspectral imagery, are generally analyzed using supervised learning approaches which requires human-expert intervention and image specific reference labelled data for training the classification algorithm. However, as the scale of image acquisition and the information demands are time-critical and involves several images per unit time, classical supervised approach fails to handle the image analyses.The spectral knowledge contained in an image analysis, in principle, can be used for analyses of imagery under broadly similar condition of space and time. With growing need of real-time image acquisition for agricultural application, there is a need for image analysis approaches that support time critical image information extraction and with minimum manual effort. In principle, knowledge gained from processing benchmark analyses tasks can be transferred across images at a different space and time, thereby speeding up the hyperspectral image analysis. This can also solve the problem of limited training data availability for hyperspectral images. Knowledge transfer has the potential to generalize hyperspectral image classification across space or time [3] [4]. In [5], the authors explored the possibility of urban buildings extraction by transferring spatial features of building objects extracted across two different images which were segmented for object-based image analysis. In [6], the authors attempted to enhance the resolution of hyperspectral images by exploiting the knowledge learned from mapping low and high-resolution natural images via deep convolutional neural networks. In [7], the authors combined data reduction and transfer learning to build feature extractors that can be applied to any hyperspectral imagery, irrespective of the sensor used. [8] exploits the potential of transfer learning for soil spectroscopy and estimates the clay content of soil using hyperspectral data. Agriculture crops have complex spectral nature. The potential for spectral transferability at the crop level is less explored. We propose a spectral matching-based transfer learning method for the classification of vegetable crops using drone-based hyperspectral imagery.

The rest of the paper is organized as follows: Section II states the problem formulation, section III is about dataset and methodology, section IV is on results and discussions and the final session concludes the paper.

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II. Problem Formulation

The work focuses on developing a model to classify target image data with no or very less labelled samples. For this, spectral knowledge, as quantified by spectral matching metrics, is transferred from labelled source hyperspectral imagery (S-HSI) to the target hyperspectral imagery (T-HSI). The S-HSI can be defined as $\{Xs_i, ys_i\}$] where Xs are the source samples and ys are the corresponding source labels and i takes the values from 1 to L, L being the total number of pixels. In our work we consider the target image T-HSI with unlabeled samples, that is, the target is defined as {Xt}. For transferring knowledge, correspondence has to be established between the source and target images. We achieved this using similarity metrics. The source and target images are compared using three different spectral similarity metrics, namely structural similarity index (SSIM) [9], normalised spectral similarity score (NS3) [10], and spectral information divergence (SID) [11].

SSIM: Structural information gives the idea of inter-dependencies among the pixels which gives information about the structure of the objects in the visual scene. Here, SSIM is calculated between each pixel vector in the target image and each of the mean pixel vector of the source image classes. The SSIM formula is given by:

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (1)$$

Where μ_x, μ_y, σ_x, σ_y, and σ_{xy} are the local means, standard deviations, and cross-covariance for images x, y; c_1 and c_2 are the channel dimensions.

NS3: NS3 combines the advantages of the Euclidean $A_{Euclidean}$ and spectral angle mapper (α) distances between two spectra. It is given by:

$$NS3 = \sqrt{(A_{Euclidean}^2 + (1 - cos(\alpha))^2} \quad (2)$$

SID: SID describes the statistics of a spectrum. Each pixel spectrum is considered as a random variable and the disparity of probabilistic behaviour between the two spectra is measured. It is calculated as the sum of relative entropy between the source and the target ($\mathbf{D}(x||y)$) and target and source ($\mathbf{D}(y||x)$).

$$SID = \mathbf{D}(x||y) + \mathbf{D}(y||x) \quad (3)$$

where ($\mathbf{D}(x||y)$) $=\Sigma_{l=1}^{L}\ p_l \log\ (\frac{p_l}{q_l})$ and p and q are the probability vectors of x and y respectively.

III. Dataset and Methodology

A. Dataset:

As part of our ongoing research activities on remote sensing for farm level crop monitoring, we acquired drone-based hyperspectral imagery over the experimental plots of University of Agriculture Sciences (UAS), Bengaluru, India in April 2018. Three vegetable crops-eggplant, cabbage and tomato were cultivated in the areas imaged by drone-based Cubert FireflEYE hyperspectral sensor. Hyperspectral images were acquired at 2mm spatial resolution with a spectral sampling interval of 4nm effectively in the 400-1000 nm wavelength region resulting in 125 bands after removing the uncalibrated and noisy bands.Each image is 1000 by 1000 pixels. An image containing all three crops is taken as the source image with ground truth labels as in Fig.1. The model is applied for three different target images obtained by the same sensor and at the same height of 30 m.

B. Methodology:

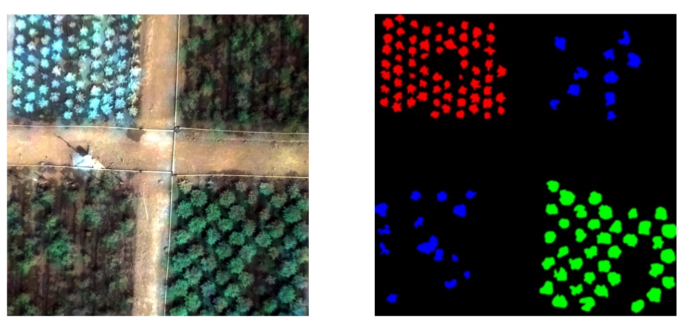
The flowchart of the proposed model is given in Fig.2. The overall process for crop classification is divided into three stages. Stage 1 is the basic classification of source image. Stage 2 is about similarity comparison and stage 3 depicts the final classification.

Stage1: The source and target images are pre-processed by removing noisy bands. Three machine learning algorithms, decision tree, support vector machine and linear regression are performed on the source image for classification. Based on the classification performance, decision tree is chosen as the base classifier,giving 96% accuracy in classification of source image.

Stage2: The mean spectral signature of each of the classes in the source domain (Fig.3) is taken for comparison with the spectral signatures of pixel vectors in the target image. Three spectral matching metrics, SSIM, NS3, SID, are used to compare the spectral signatures. For each of similarity metric, a threshold is set and based on this threshold value, the target samples are labelled. If the threshold criterion is not met, the samples are labelled zero.The class label that gives the maximum value for SSIM and minimum values for NS3 and SID between the mean spectral signature and target pixel vector is chosen for each pixel in the target image. This results in three labelled output images.

Stage3: For each pixel, the majority label among the three classified output images for that pixel is chosen as the final label for the target image. The classified image is thus obtained.

The proposed algorithm is named as spectral matching-based transfer learning (SMTL).



(a) (b)

Fig. 1: (a)) True colour composite of the source image (S-HSI) (b) Ground truth image.

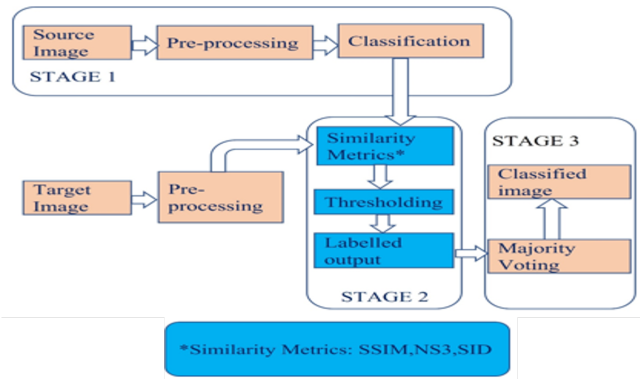


Fig. 2: Overview of the proposed model

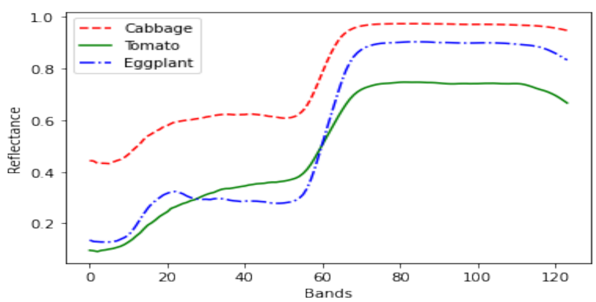


Fig. 3: Mean spectral signature of source classes

C. Validation Set:

For validating the model, ground truth data is prepared for the target image. The classified image is compared with this ground truth for assessing accuracy. The ground truth for the target image of only cabbage crop consists of 1,35,013 cabbage pixels, and the rest are unclassified. Ground truth for the target image of only eggplant crop has 3,00,265 eggplant pixels and that of tomato consists of 1,66,952 pixels. The multi-crop image has 57,948 pixels representing cabbage, 86,535 pixels representing eggplant and 22,227 pixels representing tomato,which adds up to a total of 1,66,710 crop pixels.

IV. Results and Discussion

The results obtained for the proposed model are presented in Fig. 4: (a) represents the true colour image of the area where cabbage is the only crop, (b) represents its corresponding classified image, (c) represents the area where only eggplant is grown, and (e), that of tomato cultivation.; (d) and (f) present their respective classified imagery. Fig. 4 (g) depicts the true colour image of the area where all the three crops are present and (h) is the corresponding classified image. Table 1 summarizes the accuracy assessment of the classification. It is observed that the single crop classification exhibits fairly higher accuracies (max: 85% for cabbage). When target image contains all the three crops, there is a reduction of accuracy (68%). However, considering the complexity of crop plant structures and enhanced illumination asymmetries in the plant level imagery, accuracy estimates of about 70% is a

Algorithm 1 SMTL

Input: Source image {Xs, ys}, target image {Xt}
Output: Classified target image

Calculate the mean spectral signature {Cs} for each class in the classified source image
Find similarity scores between Cs and target pixel using SSIM, NS3 and SID.
for $i = 0, 1, 2, \ldots, N$(no. of pixels in target image) and $j = 1, 2, \ldots, C$(no. of classes) **do**
    SSIM[i,j]← Eq. (1)
    NS3[i,j]← Eq. (2)
    SID[i,j]← Eq. (3)
end for
for k = 0,1,...,size (SSIM), p =0,1,...,size (NS3),q = 0,1,...,size (SID) **do**
  if $max(SSIM) > threshold1$ **then**
    $m(k) \leftarrow argmax(SSIM)$
  else
    $m \leftarrow 0$
  end if
  if $min(NS3) < threshold2$ **then**
    $m1(p) \leftarrow argmin(NS3)$
  else
    $m1 \leftarrow 0$
  end if
  if $min(SID) < threshold3$ **then**
    $m2(q) \leftarrow argmin(SID)$
  else
    $m2 \leftarrow 0$
  end if
end for
for $i = 0, 1, \ldots, N$ **do**
  ml← majority(m[i], m1[i], m2[i])
end for

substantial quality of crop classification. The lower accuracy for tomato and eggplant as compared to cabbage may be due to the fact that the mean spectral signatures of tomato and eggplant are more similar to each other than that of cabbage. Hence some of the actual pixels in each case may have been misclassified. Since the initial labels are obtained from the source image, mislabeled pixels in the initial stage of knowledge transfer may also affect the actual classification results.The threshold set for the three similarity metrics can

TABLE I
Accuracy Assessment of Transfer-Learning based Crop Classification

Target Image	Crop Samples in ground truth	Accuracy(%)
Cabbage	1,35,013	85.15
Eggplant	3,00,265	75.81
Tomato	1,66,952	70.02
Multicrop	1,66,710	67.83

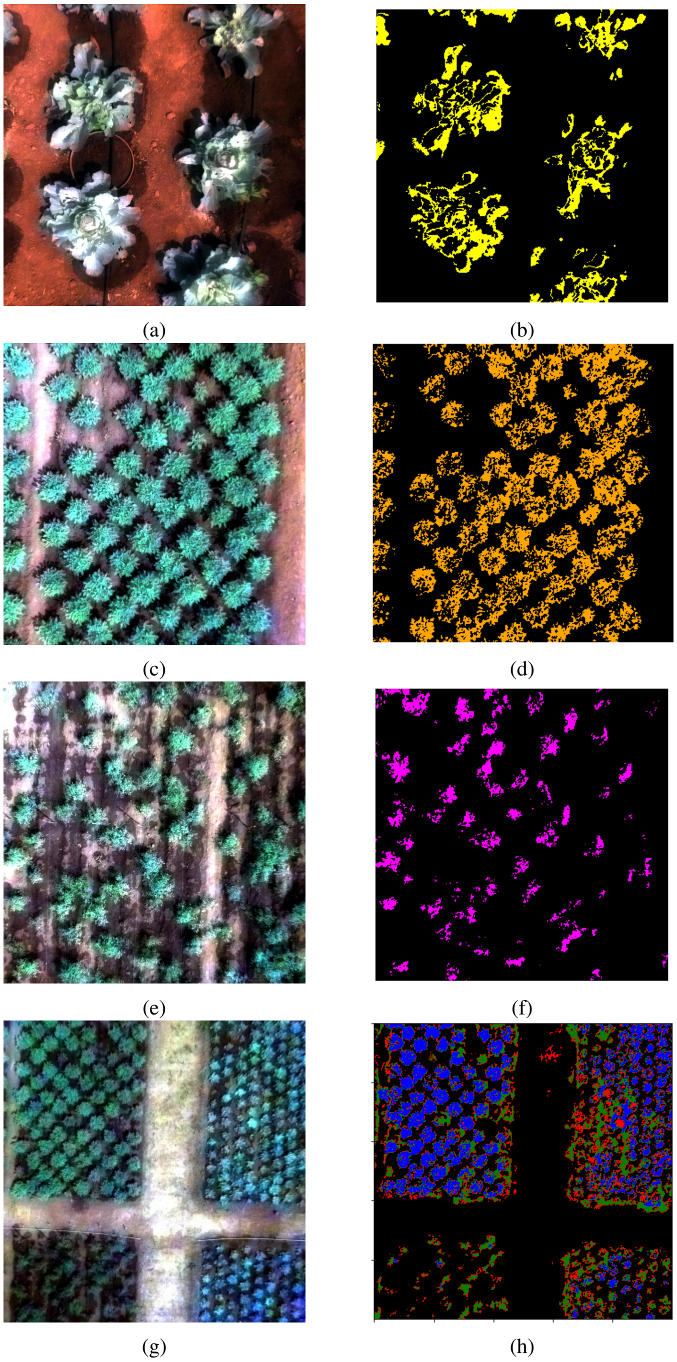


Fig. 4: Transfer-learning based classification of crops at plant level; (a), (c), (e) represent true colour composites of target images, and (b), (d), (f) represent the corresponding classified images of cabbage, eggplant, tomato, (g) and (h) are respectively the area with multi-crops and corresponding classified image

also affect the classification accuracies. For the multi-crop image, the accuracy is satisfactory, since we are comparing only the spectral signatures of the source mean classes, and the target pixel signatures. However, considering that the target samples are completely unlabeled, and the initial labels are obtained from the source, the accuracy results are satisfactory.

V. Conclusions

Technology-assisted precision agriculture is a vital component for the economic development of any country. For near-real time processing of hyperspectral data at the crop-level, transfer learning proves to be a useful tool. The proposed work focuses on spectral-matching-based transfer learning,SMTL, for classification of hyperspectral drone imagery of agricultural area consisting of three different crops cultivated in the rabi season-eggplant, tomato and cabbage. The results show that the proposed method gives fairly good performance when images containing single crops are taken as the target. The model's performance is satisfactory when multi-crop image is taken as the target. Future works include extending the model for multi-class images and also to images acquired by multiple platforms.

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