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Deep Learning based Fusion of LiDAR Point Cloud and Multispectral Imagery for Crop Classification Sensitive to Nitrogen Level

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***Abstract*—Deep learning techniques have been evolving at a faster pace offering a common framework for developing models for various applications using remote sensing data. Availability of high resolution LiDAR point cloud and multispectral imagery offers structural and spectral features vital for identifying different crops exhibiting similar spectral similarities. Our work explores the potential of deep machine learning approach for the fusion of ground based terrestrial LiDAR point cloud and satellite-based multispectral imagery for three important horticulture crops, viz cabbage, eggplant and tomato at three different nitrogen (N) levels. The core idea is evaluating the discrimination potential of the crops considering the inherent nature of nutrient effects on the crop growth. The challenges in this study are (i) horticulture crops are relatively lower in height and lack sturdy geometric profiles, (ii) crop identification of a single crop at three N levels requires discernible self-derived features in the Deep Learning (DL) based model. Contrasting with the results obtained network (LiDAR and multispectral), the deep Convolution Neural Network (CNN) exhibits substantially higher discrimination performance on the fused dataset when sensitivity to N level is not considered. Considering the sensitivity to N level, results from using LiDAR point cloud alone are comparable with the fused dataset.**

Keywords— LiDAR point cloud, multispectral imagery, data fusion, nitrogen levels, deep learning, CNN

I. INTRODUCTION

Site-specific agriculture aka precision agriculture is an innovative approach for farm management improving crop performance and productivity [1][2]. It offers a multi-dimensional approach to improve farming practices in terms of environment safety, food security, increased throughput, profit and economic growth. Precision agriculture needs application of technologies, methods and principles to detect and manage within field spatial and temporal variability and simultaneously avoid the usage of non-natural chemical fertilizers thereby decreasing environmental footprint [3]. This mode of agricultural practice allows farmers to manage variability at scales that are within a defined farm unit (e.g. section, quarter section) and target specific spatial regions of the farm unit.

Within a farm field, variability exist in terms of growth, soil nutrition and yield [4]. Therefore, there exist a better crop yield in some parts of the field when compared to the other field patches. This arises due to difference in soil, shade, slope etc. Hence the within crop diversity should be addressed at plant or patch level for better crop throughput. For this purpose, the remote sensing data obtained should be able to identify the crop at individual level. High resolution remote sensing data is a partial solution for this, but at the same time the need of the structural features for crop modelling is equally important. There has been increasing popularity and efficiency in the classification approaches on ensemble-based and deep learning (DL) techniques using multi-sensor data [5]-[8]. DL has made radical shift in the feature construction and representation and eliminated the need for the synthesis of handcrafted features for classification, object detection etc. Thus DL has been revolutionizing the future of big remote sensing data processing for various applications. Addressing the field-level spatial heterogeneity forms the locus point of precision agriculture. There is a growing relevance for automated identification of plant in precision agriculture.

Integration of information from heterogeneous datasets helps to exploit the advantages of each dataset and simultaneously suppress the disadvantages associated with each. The LiDAR (Light Detection and Ranging) remote sensing technology has the potential to provide information on canopy structural parameters such as canopy height, area, stem volume etc., since it provides vertical structure of crop canopy in complementary to the optical imagery. The incorporation of laser technology in the remote sensing field has witnessed the ability of LiDAR to make direct measurements of ground and above ground elevations with higher accuracy [9]. Thus, LiDAR can provide complementary measurements of the plant structure, which is essential when the focus is on crop discrimination at finer spatial scale. Conversely, very high-resolution multispectral imagery can provide information on crop spectral discrimination and, to a limited extent, nutrient status [10]. Therefore, it is advantageous to use both spectral and LiDAR remote sensors in unison for crop discrimination a at a fine scale. The objective of this study is therefore integrating data from high resolution multispectral satellite imagery and Terrestrial Laser Scanner (TLS) based LiDAR data, generally point cloud, for classifying three important horticulture crops – cabbage, eggplant and tomato at varied level of N at patch level. This study addresses multiple aspects of using the datasets such as identification of crops based on N status, effect of discrimination with and without fusion and utilizing the fast evolving deep learning technique to classify crops at finer scale.

II. STUDY AREA AND MATERIALS

A. Study site

Rapid growth in urbanization in Bengaluru has seen transformations which affect the quality, diversity and scale of agricultural crop production and spatial crop growth patterns. This work is part of a coordinated research aimed at the application and integration of high-resolution terrestrial and satellite remote sensing technologies to recognize the subtleties of the rural-urban impact on crop cultivation and technological approach for optimum agricultural throughputs as a function of the nutrient application to the fields. A crop growing experimental setup was established in 2017 at the University of Agricultural Sciences (UAS), Bengaluru, India. The study area is situated in the geographical coordinates 12°58’20.79’’N, 77°34’50.31’’E having a mean sea level height of 920m.

B. Experimental design

Two crop growing seasons were setup which followed the two major growth season cycles typical to India: Rabi (January-May) and Kharif (June-October). This study for vegetable crop discrimination has been conducted during the Rabi season. The crops cultivated are cabbage (Brassica oleracea L.), tomato (Solanum lycopersicum L.), and eggplant (Solanum melongena L.). The cultivars that were used for the study purpose followed the trend similar to that exercised by the farmers in and around the Bengaluru region.

The experimental fields followed a multi-cropping pattern divided into 12 plots of 12m x 18m dimension, which were subdivided into 36 sub-fields of dimension 6m x 12m with four repetitions for each crop. To study the effect of crop’s growth response to N application, each sub-plot was treated with the N fertilizer at levels viz low, medium and high. For this, urea was supplied to the crops as N source, for the medium at the rate of 46 kg N ha^{-1} for tomato, 60 kg N ha^{-1} for cabbage, and 50 kg N $ha^{-1}$for eggplant. Accordingly, a 50% more N applications are referred to as ‘highN’ and 50% less as ‘lowN’. Also, the other two macro-nutrients of NPK, phosphorous (P) and potassium (K) were also applied to the crops at the sowing time.

III. METHODOLOGY

Figure 1 illustrates the methodological framework used for the experimental implementation of the aim of the work. For the fusion of data from the two sensors, we adopted pixel level fusion. Overall, the methodology comprises of data acquisition, pre-processing, canopy height model development from LiDAR point cloud, pixel based fusion of optical and LiDAR imagery followed by deep CNN based classification of the crops at varied nitrogen levels.

Multi-scan 3D LiDAR observations were acquired using TLS (model: Faro Focus 350s) on May 2017. These multiple scans were registered to form a single 3D point cloud database using sphere fit algorithm via detection of tie points followed by registration. This point cloud was further subjected to ground filtering to classify the data as ground and non-ground points using the progressive triangulation irregular network (TIN) densification (PTD) [11].

In order to bring the 3D data with the elevation information from the mean sea level, after PTD it was normalized with respect to the ground. Thus, each point in this geo-referenced 3D representation has height information from the ground level. For the construction of Canopy Height Model (CHM), the non-ground points were rasterised with a cell dimension of ***n*** x ***n*** where the step size n = 0.5 was used [12]. Development of CHM involves two steps: (1) identification of crop top, and (2) segmentation of plant crown. The crop top was identified using an adaptive filtering technique, variable window filter (VWF) [13]. To perform the segmentation of the crop crown, object oriented marker-controlled watershed segmentation was used [14], where the identified crop tops were considered as the markers.

Correspondingly, very high resolution multispectral imagery from the WorldView – III satellite was acquired during May 22, 2017 with panchromatic and multispectral bands at 2m and 0.5m spatial resolution respectively. The imagery was atmospherically corrected using flexible atmospheric compensation technique (FACT) [15] and further pan-sharpened using Grand-Schmidt image fusion method [16] to 0.5 spatial resolution.

After the pre-processing of LiDAR and WV-III and rasterization of LiDAR point cloud for the classification of the crops a pixel-based fusion strategy was followed. Both the imageries are co-registered pixel-wise at 0.5m resolution. We designed a 2D deep convolutional neural network (DCNN) for crop classification. For ingesting the fused dataset into this DL framework, the data has to be prepared. The classification is to be performed at medium, low and high N values (as described in 2.1.2 section). The 36 sub-fields belonging to nine classes were aggregated together based on the crops. Then the crops were divided into 700 subsets each of dimension 7 x 7 x 5 based on N, thus giving 9 crop classes as shown in Figure 3. Since the DCNN is reliant on large training set to improve the models’ performance and avoid the phenomenon of overfitting, the generated subset of each class was subjected to data augmentation. The train, validation and test set ratio followed for this experiment was 80:10:10.

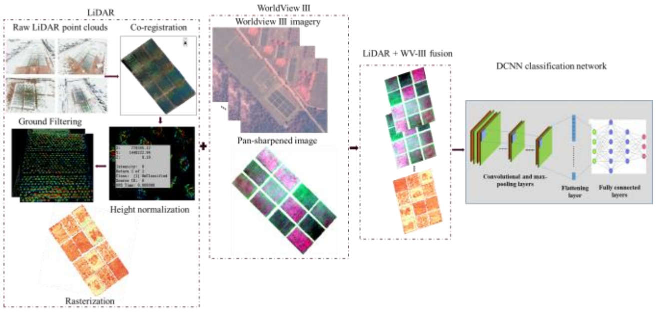


Fig.1. Overall methodology flowchart adopted for deep learning based classification of crops at different levels of N.

Data augmentation in computer vision refers to increase the size of the data set by creating modified image versions through various geometrical transformations such as shift, rotation, flip, zoom etc. Here the subset set was processed for rotation at angles 90^0 and 180^0. The values in the spectral bands were digital numbers (DN), thus prior to augmentation, the DN values where normalized with the maximum value in each band.

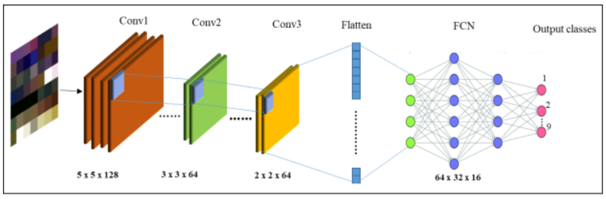


Fig.2. Top-level overview of DCNN architecture designed for crop classification with specific reference to N levels.

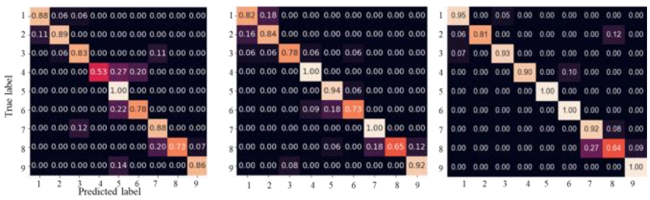
The core element of this model is the DCNN based classification. The n x 7 x 7 x 5 was given as input to the 2D convolution layer. The 2D convolution understands the spatial context of the input imagery and is able to produce better classification result in comparison to pixel level approach. The architecture adopted has three convolution layers of size as described in the Figure 2, where conv layer is given the activation function ReLu (Rectified Linear Unit). In contrast to the traditional way of applying maxpooling after each conv layer, here the feature aggregation was performed after all the conv layers. The layers were flattened into single dimension as a latent representation and fed into the fully connected layers to produce the 9 classes of crop at different N.

To prevent the problem of over-fitting that is typical to the deep learning algorithms, dropout was strategized with probability 0.5 and, learning rate exponential decay techniques and to generalize the loss function. For optimization of loss function, adaptive moment estimation (adam) optimizer was used which has faster convergence rate.

IV. RESULTS

A deep convolution neural network was used for the classification of the crops with explicit reference to different levels of N. The idea was to evaluate if there is any discernible improvement in the discrimination of the crops considering the implicit nature of nutrient effects on the crop growth. Apparently, crop discrimination within the same crop at different N levels is evidently present in the case of individual sensor classifications of WorldView-III and LiDAR. Results of the validation of the deep CNN based classification of the fused dataset are shown in Figure 3 and Table 1.

For comparative performance, the deep CNN model has also been applied on WorldView-III and LiDAR point cloud independently. As evident from Table 1, the classification



(a) (b) (c)

Fig. 3. Confusion matrix showing the deep CNN based classification of crops using data (a) WorldView-III, (b) LiDAR point cloud, and (c) WorldView-III + LiDAR point cloud. The classes corresponding to the labels numbered 1 to 9 are cabbage high, cabbage low, cabbage medium, eggplant high, eggplant low, eggplant medium, tomato high, tomato low, tomato medium respectively.

TABLE 1: SUMMARY OF THE ACCURACY ESTIMATES OF THE CLASSIFICATION OF CROPS AT DIFFERENT N LEVELS USING DEEPCNN APPROACH.

Data type	Kappa Coefficient (%)	Overall accuracy (%)
WorldView-III + LiDAR point cloud	91.1	92.1
LiDAR point cloud	83.9	85.5
WorldView-III	80.6	82.9

performance of the deep CNN indicates two distinct features. The first observation is that the overall accuracy of crop classification with independent datasets WorldView-III and LiDAR point cloud by lesser by 8-10% in comparison to the fused dataset. The second observation is that the independent classification accuracy of the multispectral imagery and LIDAR point cloud is in the same range. However, a remarkable feature of the classification of the fused dataset using deep CNN is that between crop discrimination has increased while exhibiting the moderate level of within crop confusion, particularly at the medium level of N.

Cabbage at low and high N levels was identified as tomato, and there is an inherent confusion between tomato within its N levels. The apparent misclassification of the cabbage would have been due to the spectral confusion resulting from the WorldView-III dataset. As evident from the Figure 3, the quality of classification is relatively poor with the WorldView-III dataset across the crops. However, as evident from Figure 3(b) the deep CNN exhibits a distinctly higher classification accuracy level with the LiDAR point cloud supporting the improvement of between-crop discrimination from the fused dataset. These observations support the prominence of the LiDAR point cloud derived structural features in discriminating crops based on N. Summarizing the deep CNN-based classification performance, an improvement of 10.5% and 7.5% is observed for the LiDAR WorldView-III datasets independently. This observation supports the premise that deep CNN based classification models exploit the spectral-geometrical features of the fused dataset produced by integrating WorldView-III and LiDAR point cloud.

V. DISCUSSION

Deep machine learning approaches have been rapidly expanding into the application base of remote sensing by offering a common methodological framework for building the models and potentially transfer across space and time. A range of problems related to data analyses such as classification, prediction, regression, clustering, and data engineering such as data fusion, multi-modal data integration has been explored. The fusion of spectral data (multispectral and hyperspectral) and LiDAR point cloud acquired from the ground, airborne and satellite platforms have been explored in the last few years. The studies have mainly reported on the fusion of data- spectral and LiDAR point cloud for improved classification of land use/land cover, buildings' footprints generation, and the classification of forest tree species (e.g. [17][18]). Our exploration of the deep machine learning approach for the fusion of multispectral imagery and the LiDAR point cloud is a distinct methodological evaluation and application for vegetable crops with explicit reference to

N levels. The challenges are: (i) crop plants are relatively short height and lack sturdy shape and profile, and (ii) response to N levels, which can be further influenced by various soil and environmental factors. The nature of the classification performance can be explained from two distinct perspectives: (i) discrimination performance within and between crops, and (ii) crop discrimination sensitivity to different N levels.

Contrasting with the results obtained from the fused dataset, the deep CNN has exhibited substantially higher performance on the independent datasets of multispectral and LiDAR point cloud when the sensitivity to N level is considered. The results are consistent across the crops with and without reference to the N status. Compared to the classification results from the WorldView-III, the overall accuracy of classification from the LiDAR point cloud is higher. This observation establishes the prominence of plant structural features for crop discrimination at the plant/patch level. Although the different versions and model architectures of the deep learning methods available in the recent literature offering various levels of sophistication and performance improvements, we can draw two stable inferences: (i) the performance of the deep machine learning based fusion of multispectral and LiDAR point cloud is higher for crop discrimination, and (ii) the discrimination with explicit reference to N status is more sensitive to within crop classes.

VI. CONCLUSIONS

This work has to study the discrimination of three vegetable crops at different N levels using multi-sensor data. For this purpose, identification of the crops at varied levels of N is classified using a deep CNN based deep learning framework. This architecture is able to identify the crops with a higher accuracy of 92% for the fused data when sensitivity to N is ignored. Improvement in accuracy with fused dataset with reference to N level is not distinctly better in comparison with individual datasets used. The model has succeeded in producing almost comparable results to individual sensor-based crop classification. The performance enhancement of the inclusion of the structural crop information along with the spatial data has been observed in the fused dataset classification. Moreover, crop classification using LiDAR data has also exhibited better results in comparison to the WordView-III classification.

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