Farm detection based on deep convolutional neural nets and semi-supervised green texture detection using VIS-NIR satellite image

Farm Detection based on Deep Convolutional Neural Nets and Semi-supervised Green Texture Detection using VIS-NIR Satellite Image

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Abstract: Farm detection using low resolution satellite images is an important topic in digital agriculture. However, it has not received enough attention compared to high-resolution images. Although high resolution images are more efficient for detection of land cover components, the analysis of low-resolution images are yet important due to the low-resolution repositories of the past satellite images used for timeseries analysis, free availability and economic concerns. The current paper addresses the problem of farm detection using low resolution satellite images. In digital agriculture, farm detection has significant role for key applications such as crop yield monitoring. Two main categories of object detection strategies are studied and compared in this paper; First, a two-step semi-supervised methodology is developed using traditional manual feature extraction and modelling techniques; the developed methodology uses the Normalized Difference Moisture Index (NDMI), Grey Level Co-occurrence Matrix (GLCM), 2-D Discrete Cosine Transform (DCT) and morphological features and Support Vector Machine (SVM) for classifier modelling. In the second strategy, high-level features learnt from the massive filter banks of deep Convolutional Neural Networks (CNNs) are utilised. Transfer learning strategies are employed for pretrained Visual Geometry Group Network (VGG-16) networks. Results show the superiority of the high-level features for classification of farm regions.

1 INTRODUCTION

Land cover classification and object-specific classification using Earth's observing satellites have been some of the most important applications of remote sensing. In digital agriculture domain, farm detection is a key factor for different applications such as diagnosis of diseases and welfare-impairments, crop yield monitoring and surveillance and control of micro-environmental conditions an important topic in digital agriculture domain (Stephanie Van Weyenberg, Iver Thysen, Carina Madsen, 2010; Schmedtmann and Campagnolo, 2015; Vorobiova, 2016; Leslie, Serbina and Miller, 2017)

There have been advancements in computer science leading to the launch of high-resolution sensors. Yet, it remains fundamental to study and use

Low-resolution satellite imagery that is being used since more than 30 years. The higher resolution offered by new sensors surely overcome the limitations related to accuracy. However, the continuity of the existing low-resolution systems data is crucial. A work reported in (Rembold *et al.*, 2013), is an example that uses low-resolution Landsat imagery for crop monitoring and yield forecasting, expanding their operational systems. Furthermore, time series investigation, for example change detection, requires comparison with low resolution images of the old databases (Canty and Nielsen, 2006; Tian, Cui and Reinartz, 2014). In addition, analysing high resolution satellite images requires more processing time and higher cost (Fisher *et al.*, 2018). As discussed in (Fisher *et al.*, 2018), the achieved accuracy can be affected by some limiting factors such as the variations in sensor angle and increase in

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shadows. Such factors challenge the precision of spatial rectification. Then, considering the trade-off between accuracy and cost, and depending on the application, the value and need for higher-resolution data must be analysed. Therefore, low resolution satellite images such as Landsat are appropriate for detection of large features such as farms (Leslie, Serbina and Miller, 2017).

Reviewing the literature shows a vast amount of research performed in land-cover classification. Early works utilized pixel-based unsupervised and supervised techniques such as Neural Networks (NN), decision trees and nearest neighbours (HARDIN. P.J, 1994; Hansen, Dubayah and Defries, 1996; Paola and Schowengerdt, 1997). Then, sub-pixel, knowledge-based, object-based and other hybrid classification techniques became prevalent. Examples can be found (Foody and Cox, 1994; Ryherd and Woodcock, 1996; Stuckens, Coppin and Bauer, 2000). In many of those works software and computational tools such as ERDAS and Khoros 2.2 were extensively utilized (Stuckens, Coppin and Bauer, 2000). Recently, eCognition and ArcGIS softwares have been utilized widely (Juniati and Arrofiqoh, 2017; Fisher et al., 2018); A review of some remote sensing classification studies can be found in (Lu and Weng, 2007), where feature extraction and, discrimination techniques for object classification, such as urban areas and crops are addressed.

One of the challenges of software-based strategies is their low accuracy when applied on low resolution images like Landsat 8 (Juniati and Arrofiqoh, 2017). In such cases, appropriate choice of training samples, segmentation parameters and modelling strategy is important; for example, suitable segmentation scale to avoid over and under segmentation is vital for Object Based Image Analysis OBIA. Although there are several reports of superior performance on different landscapes, due to the segmentation scale issue and lower resolution, OBIA is not very ideal for Landsat data (Juniati and Arrofiqoh, 2017).

Another group of strategies utilise saliency maps for pixel level classification of high-resolution satellite images mainly. Examples are spectral domain analysis such as Fourier and wavelet transforms for creation of local and global saliency maps (Zhang and Yang, 2014; Zhang et al., 2016) and combined low level SIFT descriptors, middle-level features using locality-constrained linear coding (LLC) and high level features using deep Boltzmann machine (DBM) (Junwei Han, Dingwen Zhang, Gong Cheng, Lei Guo, 2015).

In addition, the state of the art CNNs have been used recently for classification of satellite images (Albert, Kaur and Gonzalez, 2017; Fu et al., 2017; Muhammad et al., 2018). Due to the limited effectiveness of manual low-level feature extraction methods in highly varying and complex images such as diverse range of land coverage in satellite images, deep feature learning strategies have be applied recently for ground coverage detection problems. One of the effective deep learning strategies is the deep CNNs due to its bank of convolutional filters that enables quantification of massive high-level spectral and spatial features.

In this paper, the problem of farm detection using low resolution satellite images is addressed. Two main strategies are considered and compared.

The first strategy is based on the traditional feature extraction and SVM classification techniques, similar example works in different domains are (Jake Bouvrie , Tony Ezzat, 2008; Sharifzadeh, Serrano and Carrabina, 2012; Sharifzadeh et al., 2013). The developed algorithm consists of an unsupervised pixel-based segmentation of vegetation area using NDMI, followed by a two-step supervised step for texture area classification and farm detection; at the first step GLCM and 2-D DCT features are used in an SVM framework for texture classification and in the second step, object-based morphological features were extracted from the textured areas for farm detection.

The second strategy utilises the deep high-level features of pre-trained CNNs. The VGGNet16 is used and the activation vectors are utilised for farm detection problem using transfer learning strategy.

The rest of paper is organized as follows; section 2 is about data description. Section 3 describes the both classification strategies. The experimental results are presented in section 4 and we finally conclude in section 5.

2 DATA DESCRIPTION

Landsat 8 is the latest earth imaging satellite of the Landsat Program operated by the EROS Data Centre of United States Geological Survey (USGS), in collaboration with NASA. The spatial resolution of the images is 30m. Landsat 8 captures more than 700 scenes per day. The instruments Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) in Landsat 8 have improved Signal to Noise Ratio (SNR) and quantization of data is 12-bit to allow better land cover analysis. The products downloaded are 16-bit images (55,000 grey levels) (Leslie,

Serbina and Miller, 2017) (*Landsat.usgs.gov. Landsat 8 | Landsat Missions*). There are 11 bands out of which, we use all the visible and infrared (IR) bands. The chosen area for analysis is near Tendales, Ecuador (See Figure 4). In this work, different combinations of band are used for calculating vegetation and moisture indices used in estimation of vegetation green areas as well as visible RGB bands for classification analysis.

3 METHODOLOGY

In this section the two main used classification methodologies are explained.

3.1 Feature Extraction-based Strategy

In this strategy, the vegetation area is segmented using the Normalized Difference Moisture Index (NDMI) image. Next, local patches are generated automatically, from the segmented green area. Then, textured areas including farms or any other pattern are classified by applying SVM on the extracted features using GLCM and 2-D DCT. Finally, the farm areas are detected by morphological analysis of the textured patches and SVM modelling. MATLAB 2018 was used for all implementations. Figure 1 shows the block diagram of the analysis strategy.
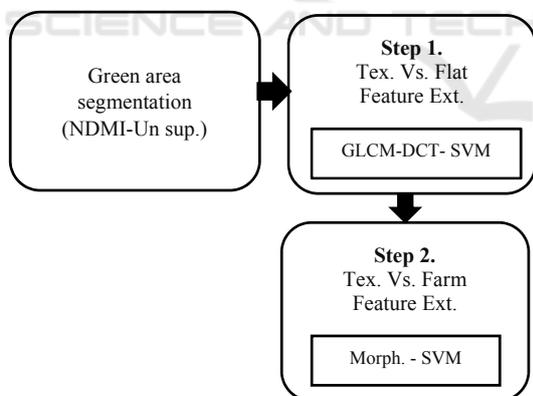

Figure 1: Block diagram showing the overall process of the first strategy.

3.1.1 Vegetation Segmentation

The pixels are segmented using spectral bands; the Near Infra-Red (NIR) in 851-879 nm range and Shortwave NIR (SWIR) in 1566-1651 nm range are used. One of the common methods for vegetation estimation is the Normalized Difference Vegetation Index (NDVI) (Ali, 2009). However, NDMI (Ji et al.,

2011) can be a more suitable technique because it considers the moisture content of the soil and plants instead of the leaf chlorophyll content or leaf area. There are also similar works like (Li et al., 2016), which have used NDMI and tasselled cap transformations on 30m resolution Landsat images for estimating soil moisture. Hence, the farm areas that went undetected by NDVI are well detected by thresholded NDMI strategy.

NDMI uses two near-infrared bands (one channel of 1.24-µm that was never used previously for vegetation indices) to identify the soil moisture content. It is employed in forestry and agriculture applications (Gao, 1996). This index has been used in this paper for the estimation of total vegetation including the agricultural lands and farms. For Lands imagery, NDMI is calculated as:

$$\text{NDMI} = \frac{\text{NIR} - \text{SWIR}}{\text{NIR} + \text{SWIR}} \quad (1)$$

NDMI is always in the range [-1, +1]. It is reported that NDMI values more than 0.10- 0.20 indicate very wet or moist soil surfaces (Ji *et al.*, 2011). Then, based on this study, cultivable land is extracted for further classification.

3.1.2 Texture Area Detection

The detected green areas from the previous step are mapped on the RGB band images. Farm areas are part of the green areas of the image; therefore, the detected green areas are divided into small patches of 200×200 pixels. Then, feature extraction is performed for each patch of image to detect the textured patches. Patches with flat patterns do not include a farm area.

GLCM - One of the feature extraction techniques employed for texture areas is the GLCM that is widely used for texture analysis (Tuceryan, 1992). The GLCM studies the spatial correlation of the pixel grayscale and spatial relationship between the pixels separated by some distance in the image. It looks for regional consistency considering the extent and direction of grey level variation. Considering the characteristics of the flat regions and the textured regions (non-farm or farm) as shown in Figure 5, GLCM is used for discrimination. Mathematically, the spatial relation of pixels in image matrix is quantified by computing how often different combinations of grey levels co-occur in the image or a section of the image. For example, how often a pixel with intensity or tone value i occurs either horizontally, vertically, or diagonally to another pixel at distance d with the value j (see Figure 2-a). Depending on the range of intensities in an image, a

number of scales are defined and a GLCM square matrix of the same dimensional size is formed. Then, image pixels are quantized based on the discrete scales and the GLCM matrix is filled for each direction. Figure 2-b shows the formation process of a GLCM matrix based on horizontal occurrences at $d = 1$. The grayscales are between 1 to maximums 8 in this case.

Two order statistical parameters: Contrast, Correlation, Energy and Homogeneity samples are used to define texture features in the vegetation. Considering a grey co-occurrence matrix p , they are defined as:

$$\text{Contrast} = \sum_{i,j} |i - j|^2 p(i,j) \tag{2}$$

$$\text{Correlation} = \sum_{i,j} \frac{(i - \mu_i)(j - \mu_j)p(i,j)}{\sigma_i \sigma_j} \tag{3}$$

$$\text{Energy} = \sum_{i,j} p(i,j)^2 \tag{4}$$

$$\text{Homogenity} = \sum_{i,j} \frac{p(i,j)}{1 + |i - j|} \tag{5}$$

where, i, j denote row and column number, μ_i, μ_j , σ_i, σ_j are the means and standard deviations of p_x and p_y , so that, $p_x(i) = \sum_{j=0}^{G-1} p(i,j)$ and $p_y(j) = \sum_{i=0}^{G-1} p(i,j)$. G is the number of intensity scales, used for GLCM matrix formation.
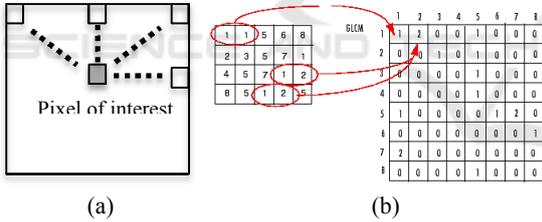

Figure 2: (a) Illustration of forming GLCM matrices in four directions i.e., $0°, 45°, 90°, 135°$. (b) Computation of GLCM matrix based on horizontal occurrences at $d = 1$ for an image (MATLAB, 2019).

Further detailed information can be found in (Haralick, Dinstein and Shanmugam, 1973). The GLCM features are calculated in directions 0°, 45°, 90°, and 135° as shown in Figure 2-a. The calculated GLCM features in the four directions are averaged for each parameter and used as input to the classification model GLCM = [Cont$_{av}$, Corr$_{av}$, Eng$_{av}$, Hom$_{av}$] , (see Table 1).

2D DCT - DCT sorts the spatial frequency of an image in ascending order and in the form of cosine coefficients. Most significant coefficients lie in the lower order, corresponding to the main components of the image, while the higher order coefficients correspond to high variation in images. Since the variation in a textured patch is higher than a flat one, the DCT map can help to distinguish them. For this aim, the original image patch I_{org} is transformed into DCT domain I_{DCT} and a hard threshold is applied to the DCT coefficients to remove the high order coefficients $I_{DCT(th)}$. Then, the inverse 2D-DCT of the thresholded image I_{iDCT} is computed. In both original and DCT domain, the reduction in the entropy of the textured patches is more significant than the flat areas representing smooth variations. Therefore, the ratio of coefficients' entropy before and after thresholding $\left[\frac{ent(I_{DCT})}{ent(I_{DCT(th)})}, \frac{ent(I_{org})}{ent(I_{iDCT})}\right]$ are calculated in both domains. For textured patches the entropy ratios are greater compared to flat patches due to the significant drop in entropy after thresholding the large amount of high frequency information (See Figure 6).

3.1.3 Morphological Features

To recognize if a detected textured patch contains farm areas, first the patch image is converted to grayscale image. Then, the Sobel edge detection followed by morphological opening and closing by reconstruction are performed. This highlights the farm areas, keeping the boundaries and shapes in the image undisturbed. Next, the regional maxima were found to extract only the areas of maximum intensity (or the highlighted foreground regions). Further, the small stray blobs, disconnected or isolated pixels, and pixels having low contrast with the background in their neighbourhood are discarded. This is because there is a contrast between the farm regions (marked as foreground) and their surrounding boundary pixels. The same procedure is performed for a non-farm sample. The area of the foreground as well as the entropy for a patch including farm is higher compared to a non-farm due to the higher number of connected foreground pixels. Figure 7 shows the resulting images of this analysis.

3.1.4 SVM Modelling

SVM classifiers are trained using the four GLCM and the two DCT features at step 1 and morphological features at step 2. The first model is capable to detect textured versus the flat patches and the second one detects the patches including farms from the textured patches with no farm areas. The LibSVM (Chang and Lin, 2011) is used. In this paper, the 5-fold cross-validation (Hastie, Tibshirani and Friedman, 2009), is used to find the optimum kernel and the corresponding parameters. It helps to avoid over-

fitting or under-fitting. The choice of kernel based on cross validation allows classifying data sets with both linear and non-linear behaviour. SVM was used for remote-sensing and hyperspectral image data analysis previously (Petropoulos, Kalaitzidis and Prasad Vadrevu, 2012).

3.2 Transfer Learning Strategy for VGGNet16

CNN is a popular classification method based on deep learning different levels of both spectral and special features using the stack of filter banks at several convolutional layers. However, training a CNN requires large data sets and heavy time-consuming computations and is prone to over-fitting using small data sets. A versatile approach in this case is transfer learning; The high-level deep features learnt over several layers of convolution, pooling and RELU using million images of massive ranges of scenes and objects are kept. That is based on the fact that the weighted combination of these activation maps of high-level features are the underlying building blocks of different objects of the scenes. While, the end layers called fully connected layers (FC) should be re-trained using hundreds of new training images. These layers are used to evaluate the strong correlation of the previous layers high-level features to particular classes of the task (in training images) and calculate the appropriate weights giving high probabilities for correct classifications. Figure 3 shows the transfer learning concept.
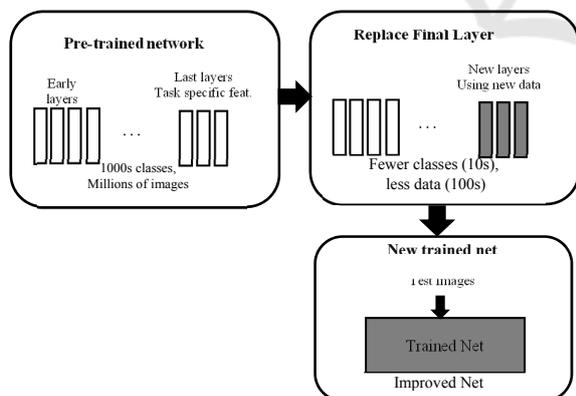

Figure 3: Block diagram showing the transfer learning strategy.

The recent works on utilisation of this technique (Chaib et al., 2017; Li et al., 2017) shows suitability

of transference of the learnt activation vectors for a new image classification task. Therefore, new patches of satellite images are used to retrain the final FC layers of VGG-16 CNN.

3.2.1 VGG-16

VGG-16 network is trained on more than a million images from the ImageNet database (*Image Net*, 2016). There are 16 deep layers and 1000 different classes of objects, e.g. keyboard, mouse, pencil, and many animals. This network has learned rich high-level feature representing wide ranges of objects. The size of input image is $224 \times 224 \times 3$ where the three colour layers are RGB bands. The last three FC layers are trained for classification of 1000 classes. As explained, these three layers are retrained using our satellite image patches of the same size for farm classification while all other layers are kept.

4 EXPERIMENTAL RESULTS

In this section the results obtained from both strategies are presented and compared.

4.1 Feature Extraction Strategy Results

As mentioned in section 2, the Landsat 8 satellite images source is used. Figure 4-a shows the image used in this work.
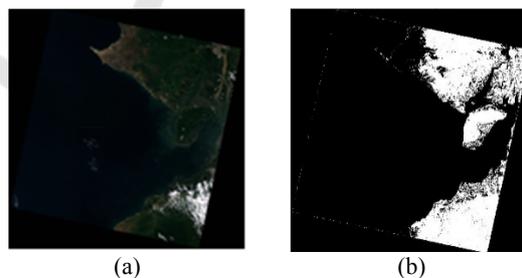

Figure 4: (a) Landsat 8 RGB image of Tendales, Ecuador (b) Result of thresholding using the NDMI.

Figure 4-b shows the result of vegetation green area detection using NDMI. This image was further utilised for making patches (from green areas) that are used for the two-step classification framework. Figure 5 shows three patches of flat, textured-farm and textured non-farm areas.
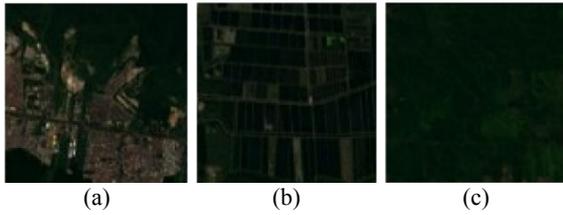
Figure 5: Examples of (a) Flat (b) Textured-Farm (c) Textured Non-Farm patches.

In the experiments of both steps of feature extraction and classification with SVM, the number of training patches of both classes (textured verses flat and farm verses non- farm) were almost balanced to avoid discriminative hyperplanes found by SVM be favoured toward the more populated class. Totally from total patches, around 75% was used for training and the rest were kept as unseen data for test. In the first classification, 111 samples were used for training and 15 samples for test. In the second classification, there were 83 training samples and 22 test samples.

At the first step, the four GLCM features and two DCT features were extracted from patches and combined. Figure 6 visualises the 2D DCT maps of a flat and textured patch before thresholding the higher frequencies coefficients and after thresholding. As can be seen, the textured patch has high energies in both low frequencies as well as high frequencies, while in the flat patch DCT map, only low coefficients show high energy values. Therefore, the thresholded DCT map of the textured patch shows significant drop of energies in high frequencies. This influences the entropy ratios.
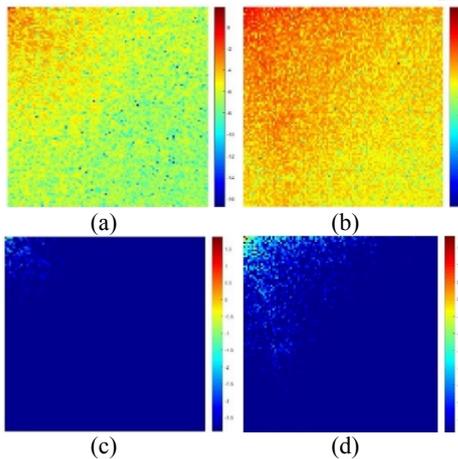

Figure 6: DCT map before thresholding (a) flat patch, (b) textured patch. After thresholding (c) flat patch (d) textured patch.

Table 1 presents the average of the GLCM and DCT features over 20 patches for textured and flat classes.

Table 1: GLCM and one of the DCT features used for classification of Flat and Textured Areas. (Values shown are averaged over 20 samples).

Class	Cont.	Eng.	Hom.	Ent.	DCT Ent. Ratio
Flat	0.0041	0.991	0.9979	3.014	0.1202
Tex.	0.067	0.847	0.9671	4.761	0.3337

All the classified textured patches from this step were used to extract the morphology features at the second step, as shown in Figure 7.
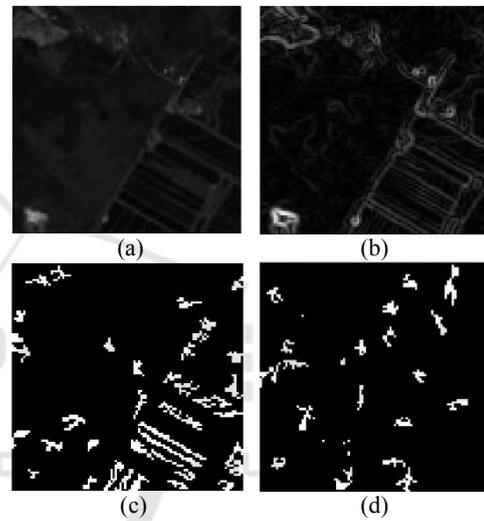

Figure 7: (a) Grayscale image of a farm patch (b) Result of Sobel edge detection (c) Detected farm area by morphological foreground detection (d) Detected area of a textured non-farm patch shown in Figure 5-a.

The performance of classifiers is evaluated based on the number of correctly classified samples. Results are presented in Table 2. As can be seen, the first texture classification step is very robust. However, the performance is reduced for the second farm classifier based on morphology features.

Table 2: Training and test accuracy of the two-step feature extraction-based strategy for farm detection.

Classification Step	Train Accuracy (%)	Test Accuracy (%)
1	96.39 (107/111)	93.33 (14/15)
2	83.1325 (69/83)	81.8182 (18/22)

4.2 Transfer Learning Strategy Results

In order to retrain the three FC layers of VGG-16 net, hundreds of images are required. Then, further number of patches were used compared to the first strategy to fulfil the requirements of this modelling strategy. Transfer learning was performed using three different sets of more than 300 patches. The first set includes image patches from any general area of the satellite image, including ocean patches, mountains, residential areas, green flat and textured areas and farms. The last three FC layers of VGG-16 were retrained for the two-class farm detection problem.

In the second set, the same number of patches were used excluding the non-green areas based on NDMI. This means the patches can include one of the flat green area, green textured non-farm area or a farm area.

Finally, in the third set of the same size, only green textured non-farm patches as well as farm ones were used.

In all three cases, 75% of patches were used for training and the remaining was used as the test unseen data. There were 72 farm patches and the rest were non-farm in all three sets. Due to random selection, the number of patches of each class are different in the generated sets. The average and standard deviation of the results over 5 randomly generated train and test sets are reported in Table 3. As expected, no significant difference can be seen between the results of the three studies. That is, the high-level features acquired from the stack of filter banks include all those spectral, special, structural and colour features extracted using the manual feature extraction strategy. Due to inclusive level of features extracted using the deep convolutional layers, the CNN results outperform the two-step feature extraction strategy.

Table 3: Average and standard deviation of the training and test accuracy of the CNN using transfer learning on the three different sets of patches.

Classification type	Train Accuracy (%)	Test Accuracy (%)
Farm vs. general areas	99.55 ± 0.64	96.76 ± 2.26
Farm vs. green areas	99.37 ± 0.76	95.95 ± 2.87
Farm vs. green tex. area	98.91 ± 0.52	96.76 ± 2.80

Figure 8, shows the confusion matrix of one of the five test sets results using the transferred CNN models. The first experiment data set, that classifies farm patches from any general patch was used. As

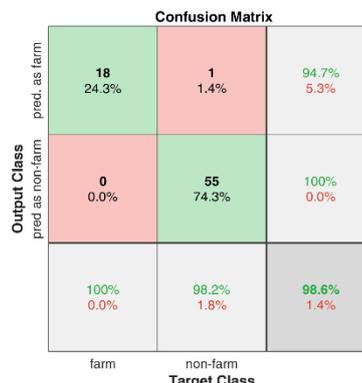shown, only one general non-farm patch was misclassified as a farm patch.

Figure 8: The confusion matrix of one of the five test sets results from the first data set (classification of farm patches from any general patch).

5 CONCLUSIONS

This paper is focused on farm detection using low resolution satellite images. Two main detection strategies are considered; first a traditional feature extraction and modelling strategy was developed. In this method, unsupervised thresholding using Normalized Difference Vegetation Index (NDVI) was used for green area detection. Then, a two-step algorithm was developed using Grey Level Co-occurrence Matrix (GLCM), 2D Discrete Cosine Transform (DCT) and morphological features as well as Support Vector Machine (SVM) modelling to detect the farms areas from textured areas. The second strategy was based on deep high-level features learnt from the pre-trained Visual Geometry Group Network (VGG-16) networks. In order to use these features for farm classification, transfer learning strategies were employed. The experimental results showed the superiority of the Convolutional Neural Networks (CNN) models.

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