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Area Estimation of Mango and Coconut Crops using Machine Learning in Hesaraghatta Hobli of Bengaluru Urban District, Karnataka

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Abstract: Timely and accurate estimation of acreage and production of horticulture crops is necessary for deciding how much, where and when to export these commodities in the national and global markets. Remote sensing has been one of the methods adopted, in addition to conventional sampling methods, for improving the estimates. Parametric image classification algorithms have been used by many researchers for identification and area estimation of horticulture crops. But these algorithms result in several unclassified pixels leading to over/underestimates. This study has been undertaken to estimate the area of two horticulture crops (i.e., mango and coconut) of Hesaraghatta *hobli* of Bengaluru urban district using Convolutional Neural Network (CNN) on Google Colaband Random Forest (RF) algorithms on Google Earth Engine (GEE). Remotely sensed data acquired by the Multi-Spectral Instrument (MSI) onboard Sentiel-2A satellite was used. Spectral signatures of horticulture crops and other associated cover types have been generated to identify the cover types and for selecting appropriate band combinations. Two different band combinations were used for area estimation of selected horticulture crops: i) Near-InfraRed (NIR), Red, and Green all three having a spatial resolution of 10 m, ii) Red edge-3, Short-Wave InfraRed1 (SWIR1) and Short-Wave InfraRed2 (SWIR2) having 20 m spatial resolution. Area estimates of horticulture crops and associated cover types were validated with respect to ground truth and statistical reports from Karnataka State Directorate of Horticulture (KSDH). It was found that the CNN model performed better than RF using NIR, Red, and Green band combination with an overall accuracy of 84%, but it failed to give similar accuracies with Red edge 3, SWIR1, and SWIR2 band combination. We attempted transfer learning using the trained CNN model at two different study areas far away from the study area and found encouraging results.

Keywords: Mango, Coconut, Area estimation, Machine learning, Convolutional Neural Network, Random Forest (RF)

1. Introduction

Horticultural crops serve as a source of income and provide employment opportunities for the farmers of the country. But these crops experience lot of fluctuation in their production owing to weather and climate variations. Therefore, timely estimates of area and production of horticulture crops are necessary for taking appropriate decisions in their marketing and export. Several researchers from Indian Agricultural Statistics Research Institute (IASRI), Directorate of Economics and Statistics (DES), Ministry of Agriculture& Farmers Welfare, National Sample Survey Organization (NSSO) and the State-level Horticulture Universities have developed innovative statistical techniques for estimating area and production but they are time consuming and costly.

Remote sensing (RS) and geographic information system (GIS) are the emerging technologies for generating quicker and easier estimates of acreage and production. Per-pixel based classification algorithms have been extensively used for estimating acreage and production of horticulture crops (Yadav et al., 2002; Nageswara Rao et al., 2004; Paul et al., 2018). Ray et al. (2018) have also tried several image analysis techniques for horticulture crop assessment under the national project called Coordinated Horticulture Assessment & Management using GeoiNformatics (CHAMAN). Advanced geospatial technologies have been applied for expansion of horticulture in the north eastern region of India (Handique et al., 2021).

Realising that the per-pixel methods do not consider the spatial relationships of neighbouring pixels associated with them which in turn results in mixed pixels and inconsistency in the estimates, several researchers tried Object-Based Image Analysis (OBIA) algorithms in the image segmentation phase followed by a variety of classification algorithms for analysis (Lu and Weng, 2007; Blaschke, 2010; Duro et al., 2012., Handique et al., 2020; Stephen et al., 2022). Baharami et al. (2021) have tried several ML algorithms to estimate crop biophysical parameters. Other researchers have tried to improve the accuracy and quality of remotely-sensed information by incorporating ancillary data in the classification process (McIver and Friedl, 2002) including expert systems and neural networks (Qiu and Jensen, 2004). However, there are not many successful studies on identification and area estimation of horticulture crops in our country. Therefore, there is a need for developing an effective methodology of incorporating spectral, spatial and ancillary information.

ML and Artificial Neural Networks (ANN) have taken over statistical modelling techniques in various fields, because of their high performance and capability to solve complex problems, by virtue of their capability to execute a particular task (Khemani, 2013). ANN has been used to classify various types of remotely sensed data and produced results better than those of traditional statistical classification methods (Jiang et al., 2004). In recent years, several researchers have used the Convolutional Neural Networks (CNN) for performing object detection, image segmentation and pattern recognition (Verma and Jana, 2019; Chouhan et al., 2022; Singh et al., 2022) and for mapping Rabi crops using multispectral temporal images of Sentinel-2A/2B sensors (Snighal et al., 2022). CNN is a deep learning algorithm and it considers shape, texture, size, and spatial relationships of objects to extract information from images.

In this study, the CNN, a widely used approach in the field of object recognition and Random Forest (RF) that is computationally less expensive and does not require a graphical processing unit (GPU), were used to develop a methodology to accurately identify and estimate the area of perennial horticulture crops (Mango and Coconut).

2.1 Study area

The Hesaraghatta *Hobli*, a sub-division below the district, in the state of Karnataka (Figure 1) was selected for the study. It is a semi-arid administrative unit having an area of 54 sq.km. It is located at an elevation of 915 meter above mean sea level (msl) and mean annual rainfall of 920 mm. This study area was selected because it has several varieties of fruit crops like Mango, Guava, Banana, Sapota, Papaya, etc developed and promoted by the Indian Institute of Horticulture Research (IIHR) of Indian Council of Agriculture Research (ICAR). The farmers of the study area are very progressive in developing horticulture as an enterprise. IIHR is encouraging farmers to maintain biodiversity in their farming systems so that their economy is climate-resilient. The study area truly represents the heterogeneity that is worth applying AI for object recognition and information extraction from remotely sensed data.

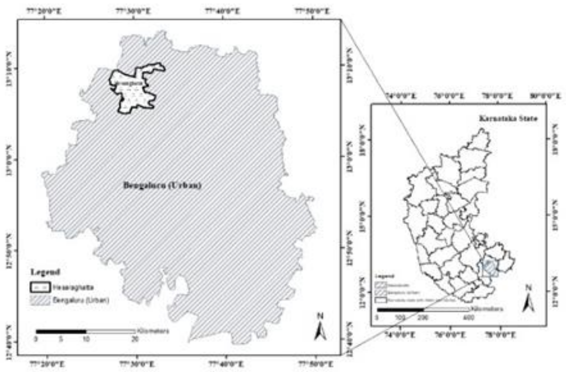

Figure 1. Location of Hesaraghatta hobli shown in the north-western corner of Bangalore Urban District

2.2 Data Sources and Software Used

Spatial data used in the study have come from different sources (Table1). We have used GEE-based cloud computing that gave access to data, algorithms to process, analyse and visualize the spatial data. The GEE had enabled us to handle several gigabytes of raw images without much financial investment on high-performance hardware and software systems. The Tensor Flow (TF), the front end Application Programming Interface (API) developed by Google has several pre-trained models. Google Colab was used as platforms to perform ML. TF, an open source framework developed by Google for predictive analytics, was used to perform deep learning. An open-source API called Keras with user-friendly interface written in Python was used to construct deep learning model on TF. Python-for-Remote Sensing-and GIS (Pyrsgis) library was used to read, write, and export geospatial data in Geotiff format. Skimage library was used for pre-processing of data.

Table 1. Sources of data used in the study

Data Sources	Data product & Date	Spatial / radiometric resolution
Sentinel-2A Multispectral Instrument (MSI)	L-2A, On UTM projection, WGS 84 datum. 23-01-2022	12 spectral bands, 10 mand 20 m / 16 bit
LULC maps from KSRSAC	Vector layers (.shp)2021	1:10,000 scale
Administrative boundaries from K-GIS website.	Vector layers (.shp)	1: 10,000 scale
Ground Truth	April 20 & 25, 2022	Geotagged Photographs
Karnataka State Horticulture Department (KSHD)	Crop Area Statistics	Printed reports

2.3 Spectral signatures of horticulture and associated cover types

Spectral signatures of mango, coconut, scrubland, eucalyptus and other plantations (Figure 2) were generated using the spectral reflectance observed in visible (B,G,R), Red edge, NIR, and SWIR bands of Sentinel-2A MSI. These signatures are very valuable in the selection of appropriate spectral bands during subsequent analysis. We observed significant overlap in spectral reflectance of mango, scrubland and eucalyptus in the wavelength range from 496.6 nm to 740.2 nm and at 864.8 nm. Good separability was observed at 835.1 nm, 1613.7 nm and 2202.4 nm. Coconut and other plantations showed significant overlap with each other from 496.6 nm to 703.9 nm and fairly good separability in other wavelengths. While the open land and fallow cropland signatures were overlapping at 560 nm and 740.2 nm, good separability was observed in other wavelengths. Signatures of grapes overlapped at 664.5 nm and that of fallow land in the 835.1 nm to 864.8 nm.

2.4 Generation of false colour composites (FCCs)

With respect to spectral signatures and in order to get familiarise with the spectral and spatial relationships in the study area, two FCCs were prepared: FCC1 using Near infrared (NIR), Red, and Green bands of spatial resolution 10 meters (m) coloured with red, green, and blue, FCC2 with Rededge-3, Short-Wave Infrared1

(SWIR1), and Short-Wave Infrared2 (SWIR2) resampled to spatial resolution of 10 m coloured with red, green, and blue respectively. These two FCCs (Figure 3 a and b) were used as input to CNN and RF for classification and area estimation of mango and coconut horticulture crops.

2.5 Generation of training samples

In order to enable the algorithm to perform the semantic segmentation (i.e., associating a label or category with every pixel in an image), we have used the land use land cover (LULC) vector map prepared by Karnataka State Remote Sensing Applications Centre (KSRSAC) for year 2021. The map has various LULC classes including mango and coconut in the form of polygons as labelled dataset (Figure 4). The LULC vectors were converted from shape file to Geotiff format with a spatial resolution of 10 metres(m) and used as training sets for analysing FCC1 and FCC2. Since the random access memory (permitted by Colab is only 12 GB), we resorted to patch based approach to generate training samples from the satellite images (Figure 5). In all 768 grids of size 64*64 pixels were used for training and validating the CNN. Each patch of image and its corresponding interpreted LULC map (mask) were used as instances in the model. In case of RF, 84 training and 35 validation samples (total 119) of minimum size of sixteen homogeneous pixels were created based on ground truth.

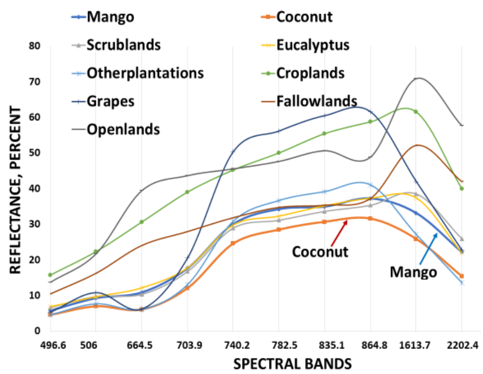

Figure 2. Spectral signature of horticulture crops and associated LULC types of study area

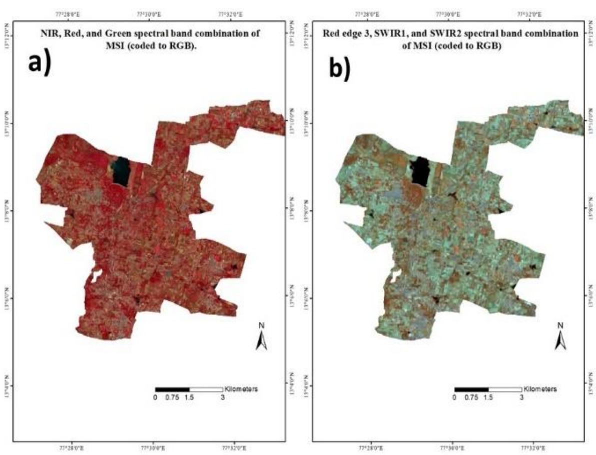

Figure 3. a) False Colour Composite (FCC)-1(all spectral bands of 10m spatial resolution) and b) FCC - 2 (all spectral bands of 20m spatial resolution)

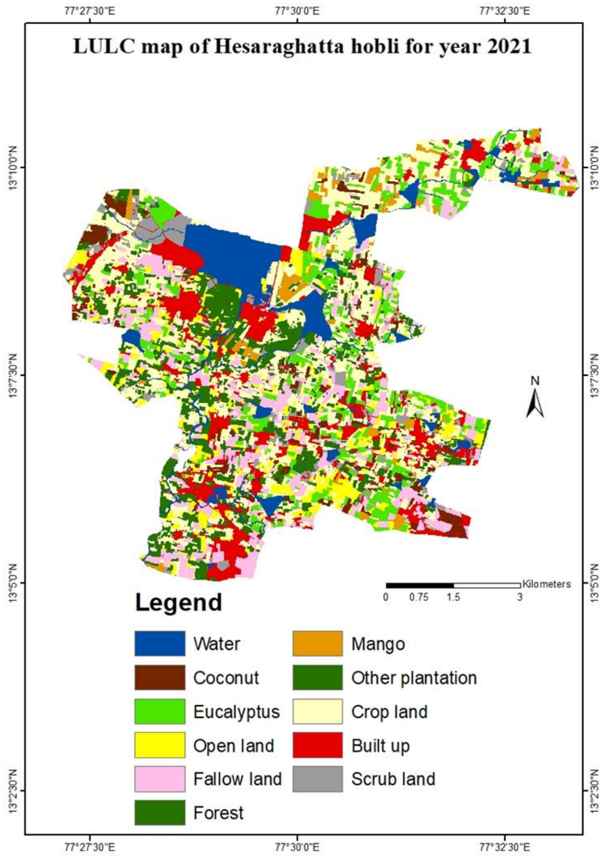

Figure 4. Reference human interpreted map of Mango, Coconut crops and associated LULC type (Source: KGIS project of KSRSAC)

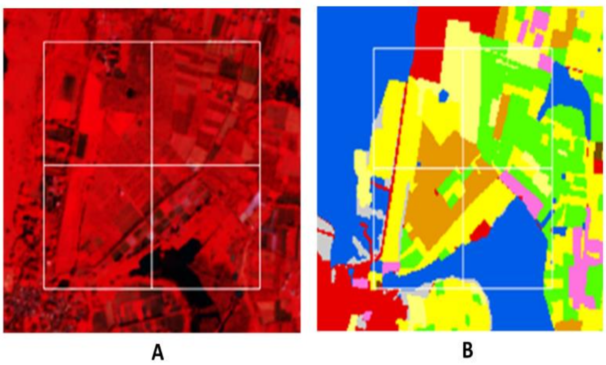

Figure 5. (A) Sample test image of size 64*64*3 and (B) Reference interpreted map (Mask) of size 64*64.

2.6 Area estimation of horticulture crops

Area estimation using RF: The ground truth collected during April 20 & 25, 2022 at 119 locations was separated into two sets of samples for training and validation. The corresponding images were extracted from MSI-Level-2A satellite data: one dataset was used to train the RF and separate dataset for evaluating accuracy of trained RF model. Sequence of steps followed for area estimation of the horticulture crops is given in Figure 6.

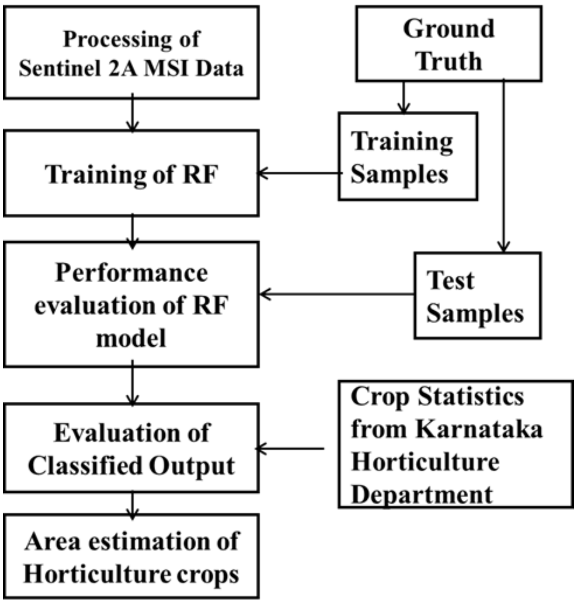

Figure 6. Methodology for area estimation of horticulture crops using RF

Area estimation using CNN: Image chips (from Sentinel - 2A MSI) and mask chips (from the visually interpreted LULC maps) were generated as explained in section 2.5. Pre-processing was carried out using MinMaxScaler of sklearn and converted the masks to categorical features using keras.utils. The data was split into training and validation datasets using sklearn.model_selection. Adam optimizer to minimise the loss, Rectified Linear Unit (ReLu) as the activation function, and several epochs to train the CNN were adopted. The Visual Geometry Group 16 (VGG16) as backbone with pre-trained ImageNet weights in U-net architecture was tried (Ronneberger et al., 2015; Shelhamer et al., 2017; Siddique et al., 2017). In the study, U-net architecture was adopted because it can extract multi-scale spatial and spectral information from remotely sensed images by performing convolution, max-pooling operation and decoding by utilising up-sampling and skip connections (Ge et al., 2021). It has achieved higher accuracies in multi-class classification tasks than other statistical and ML algorithms (TeluguntLa et al., 2018; Belgiu et al., 2016). A moving window of size 64*64 pixels with a minimal overlap of 2 pixels was used with the trained CNN model on the whole image to obtain the classified map. The final classification map was visualised using Matplotlib library and exported using a geospatial python module called Pyrsgis. Only when the validation accuracy exceeded 80%, the model was used for prediction. After training and validating the model, it was also used to perform transfer learning (i.e., testing the efficiency of the model outside the study areas). Sequence of steps followed is in figure 7.

2.7 Accuracy Assessment

Overall classification accuracy in case of RF was assessed as per Congalton and Green (1999) wherein a confusion matrix was created to evaluate and understand the performance of the classifier with both band combinations (FCC1 & FCC2). The diagonal values in the confusion matrix correspond to number of pixels classified correctly. Kappa co-efficient, producer's and user's accuracy were also evaluated from the confusion matrix. In case of CNN, accuracy graph was generated for train and validation data to evaluate the performance of the model and loss graph was generated to evaluate how far is the predicted output with respect to expected output for both band combinations. More details are available in Helber et al. (2017). A comprehensive review of assessing the labeling results can be found in Liu et al. (2018).

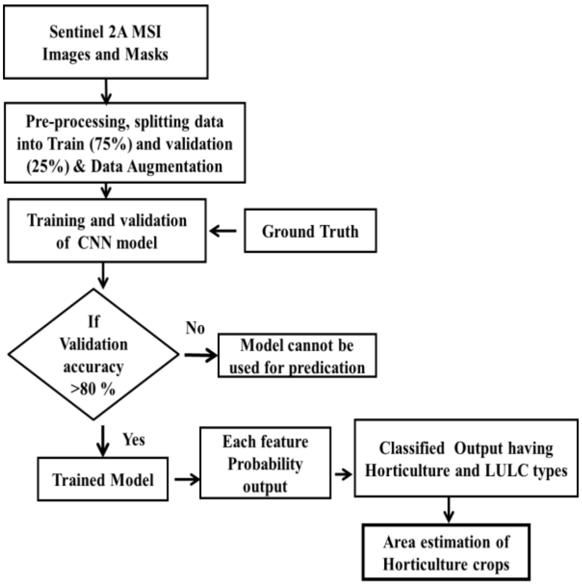

Figure 7. Methodology for area estimation of horticulture crops using CNN

3. Results and discussion

It was observed that the CNN performed better (Table 2 & Figure 8) than RF on FCC1 (10 m spatial resolution) with an overall accuracy of 84% (Figure 9). It seems this algorithm efficiently incorporates the spatial relationships among pixels along with their spectral reflectance in the classification. In case of FCC-2, the performance of CNN was not that good as seen from training and validation accuracy (Figure 10). Hence no further experiments were conducted on FCC2 with CNN. However, the RF performed better (Figure 11) than CNN on FCC2 (20m spatial resolution) with an overall accuracy of 97.65% (Table 3). The CNN was not able to generalise the smaller features within the scene (due mixed pixels) due to coarse resolution, hence resulted in lower accuracy and greater loss.

Table 2. Overall Classification accuracy of RF and CNN using FCC1 and FCC2 of MSI data

Algorithm Used		Overall accuracy (%)	Kappa coefficient
RF	FCC1	82.30	0.80

	FCC2	97.65	0.96
CNN	FCC1	84.00	0.81
	FCC2	50.55	0.48

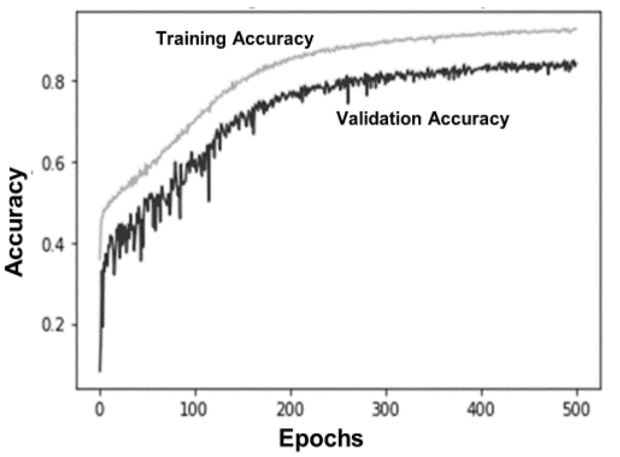

Figure 8. Training and Validation accuracy assessment graphs of CNN on FCC1

Validation of predicted classes (Figure 12) obtained using different band combinations of MSI with RF and CNN algorithms was done with respect to ground truth. As evident from Table 3, mango was identified with an accuracy of 77.7% using CNN (applied on FCC1) and RF (applied on FCC2). Validation accuracy of 100% for coconut was observed with CNN applied on FCC1 while the RF gave an accuracy of 75% and 87.5% for both band combinations. Accuracy of 57-90% was observed for other cover types with both the classifiers.

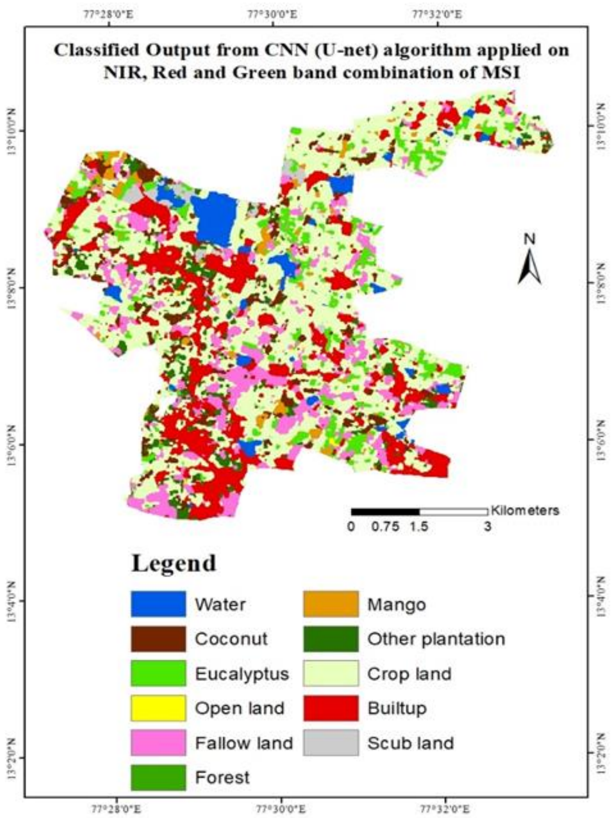

Figure 9. Classified Output using CNN (on U-net architecture) algorithm applied on FCC1

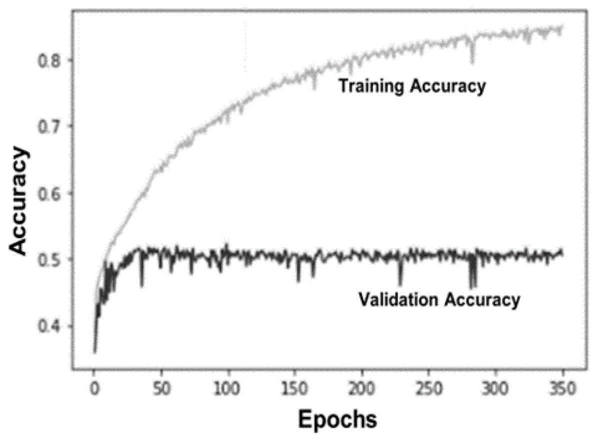

Figure 10. Training and Validation accuracy assessment graph of CNN on FCC2

Table 3. Horticulture Crop Accuracy Assessment using RF and CNN on FCC1 and FCC2

Horticulture / Associated cover types		Accuracy Using RF (%)	Accuracy Using CNN (%)
Mango	FCC1	44.4	77.7
	FCC2	77.7	
Coconut	FCC1	75.0	100
	FCC2	87.5	
Eucalyptus	FCC1	80.0	90
	FCC2	90.0	
Scrub land	FCC1	57.1	71.4
	FCC2	71.4	

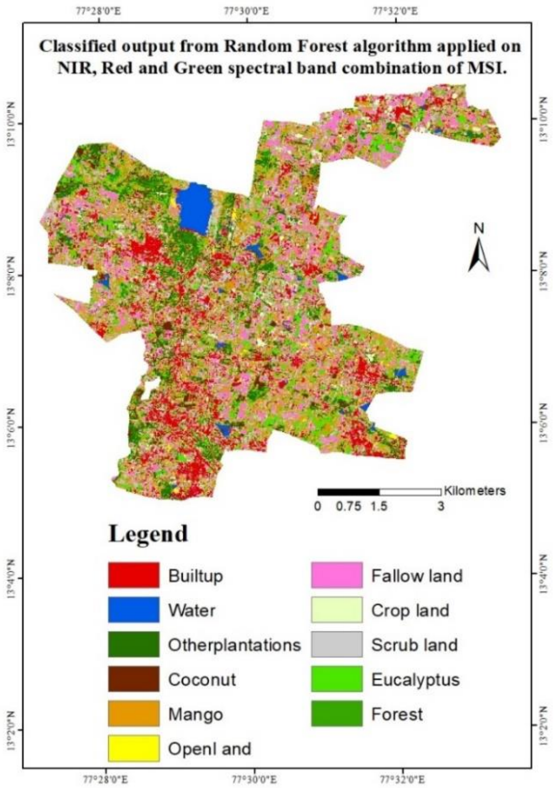

Figure 11. Classified output using RF algorithm applied on FCC1

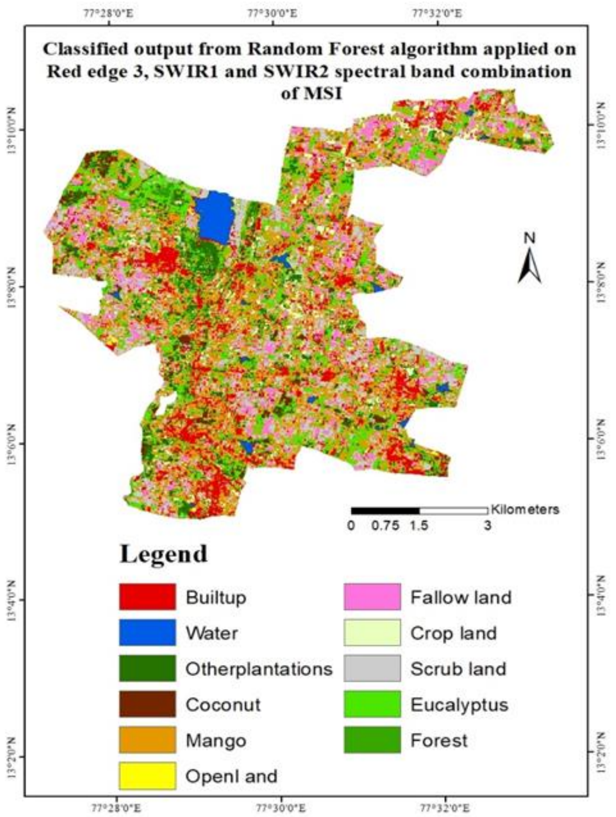

Figure 12. Classified output using RF algorithm applied on FCC2 of MSI data

As evident from Table 4, the area estimation of mango using RF classifier with both band combinations were found to be overestimated, whereas area estimation using CNN (applied on FCC1) was found to be better than RF because of no mixed pixels. The area estimates of coconut were in the range of 314-357 ha using RF with both band combinations, whereas area estimates using CNN with FCC1 data was found to be 310 ha. The relative deviations (RD) are very high because the data supplied by the KSHD are older than RS data and not updated. Our efforts to get exact data from KSHD corresponding to MSI data did not succeed.

It is very encouraging to note that the trained CNN model was found to perform reasonably good transfer learningon two different study areas viz., Kundanahobli of Devanahalli taluk of Bengaluru rural district and Bommathanahalli panchayath of Pavagada taluk of Tumkur district (location maps of these study areas not shown due to space constraint). In the first case, where spatial and spectral variabilities are similar to the study area, the model did better classification of all LULC cover types including mango and coconut horticulture crops. In second case where spatial and spectral variabilities are quite different from that of Hesaraghatta hobli (the present study area), the trained CNN model gave better classification for the cover types which were large in size (in terms of area and contiguity of classes), whereas model failed to identify smaller sporadically distributed fields. This assessment was made based on visual comparison of the predicted output with Google satellite imagery as a reference. Quantification of transfer learning, in terms of overall accuracy, omission and commission errors shall be done in our future research studies.

Table 4. Area estimates using RF on FCC1 and FCC2 and using CNN on FCC1of MSI Data

Crop Cover type		Crop Area (ha)			RD1 %	RD 2 %
		RF	CNN	KSHD @		
Mango	FCC1	1221	125	64	(+) 94.7	(+) 48.8
	FCC2	1652	-		(+) 117.4	
Coconut	FCC1	357	310	118	(+) 66.94	(+) 61.9
	FCC2	314	-		(+) 62.42	

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Relative Deviation with RF (RD1)={(RS-KSHD) / RS)} * 100., Relative Deviation with CNN (RD2)

4. Conclusions

The CNN-based classification allowed better object detection and improved classification accuracy with 10 meter spatial resolution data. In case of coarse resolution data (20 meter), the CNN algorithm showed good learning accuracy but resulted in low validation accuracy which clearly shows that there was lot of spectral mixing of horticulture gardens which are smaller than the spatial resolution of the sensor. However, the CNN model did well in identifying the built up, water bodies, fallow and other croplands which are large in spatial extent. While the RF-based classification performed well on the coarse resolution (20 m) data, though there were mixed pixels.

The study clearly shows that the ML algorithms provide a means of obtaining rapid and automatic estimation of horticultural crops like mango and coconut that are economically important. The new methods of information extraction from remotely sensed images help in the development of intelligent horticulture information systems to take appropriate decisions in export/import of these commodities and improving the efficiency of their supply chain. It would also help the state-level functionaries (e.g., KSDH) to update their area statistics without much waiting for receiving the information through their administrative hierarchy. The modern algorithms such as ML and deep learning (DL) provide better opportunities for efficiently processing the 'big data having very high spatial (a few centimeters) and temporal resolution (any time) going to be collected by several start-ups using Unmaaned Aerial Vehicles (UAVs).

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