

Enhancing remote sensing satellite image classification through parameter optimization in hybrid CNN-LSTM model

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Abstract

Satellite imagery is a vital resource in Earth observation, offering valuable insights for applications ranging from environmental monitoring to disaster response. In the pursuit of accurate and robust classification, we present a study focused on parameter optimization within the framework of hybrid Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) models. This research seeks to maximize the potential of hybrid CNN-LSTM architecture, which inherently combine spatial feature extraction capabilities of CNNs with LSTM's ability to model temporal dependencies. We delve into a systematic exploration of hyper-parameters, including the number of CNN layers, LSTM units, learning rates, and dropout rates, fine-tuning them to achieve peak classification performance. These parameters are meticulously adjusted and validated on a diverse and representative satellite image dataset. Beyond hyper-parameter optimization, we address the challenge of class imbalance frequently encountered in satellite image datasets. By incorporating specialized techniques during the optimization process, we mitigate class imbalance effects and bolster the model's accuracy. The study's findings not only unveil optimal parameter configurations but also shed light on the intricate interplay between architecture complexity and model

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performance. The resulting optimized hybrid model demonstrates exceptional classification accuracy, validating its applicability to real-world remote sensing tasks.

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1. Introduction

Remote sensing is a powerful technology that allows us to collect information about the surface of the Earth and its environment from some distance, typically from sensors on aircraft or satellites. It plays a crucial role in various fields, including environmental science, geology, agriculture, forestry, urban planning, disaster management, and more. Remote sensing relies on the detection and measurement of electromagnetic radiation (usually in the form of light or other wavelengths) reflected or emitted from objects and surfaces on Earth [39, 40].

Remote sensing, coupled with satellite imagery, enables the classification of land cover and land use types through a combination of data acquisition, preprocessing, segmentation, feature extraction, classification algorithms, and post-processing. Remote sensing technology continues to advance, with improved sensors, higher-resolution imagery, and more sophisticated analysis techniques. These advancements have expanded its role in addressing environmental challenges, supporting sustainable development, and aiding decision-making processes across various sectors [1-14].

Problems Associated with Classification

Satellite image classification is a valuable technique used in a wide range of applications, but it also comes with several challenges and problems that need to be addressed such as satellite images contain mixed pixels, where a single pixel may represent a combination of different land cover types or objects. This can make it challenging to assign a single class label to each pixel accurately [39].

In many satellite image datasets, certain land cover classes may be underrepresented, leading to class imbalance. Models trained on imbalanced datasets may exhibit bias towards overrepresented classes [40].

Over fitting occurs when a classification model learns random variations or noise in the training data and unseen data.

Acquiring labeled training data for satellite image classification can be expensive and time-consuming. Limited training data can lead to suboptimal model performance, particularly for rare or fine-grained classes [1-5].

Some land cover classes may have similar spectral signatures, making it difficult for classification algorithms to distinguish between them [39-41].

Cloud cover and atmospheric conditions can obstruct satellite imagery, leading to missing or degraded data. This can impact the accuracy of classification, especially in regions with frequent cloud cover [33-35].

Satellite images can contain noise, artifacts, and distortions caused by factors like sensor errors, atmospheric scattering, and geometric inaccuracies. These issues can affect classification results [11, 12].

Related Work

Many countries worldwide, including India, now depend on the satellite data and imagery for various purposes like quantitative analysis of the images and the preparation of thematic maps. The basis of analysis is to correlate spectral properties of an object to the digital number recorded by a sensor. This method is commonly referred to as digital image classification, as the images acquired are in digital format.

Resource allocation, environmental impact assessments, and other socio-economic applications are only a few of the many uses of digital picture classification that the Remote Sensing Alliance has developed. The step up of right algorithms for classification and accuracy assessment has lead to considerable assurance in pulling out of information and generation of thematic maps [1-14]. However, many factors affect the classifying data into a thematic map such as selection of proper data, processing of image, classification approach, which may affect the success of the classification.

This research will describe how remote sensing data with uncertainty are handled with CNN, LSTM and hybrid CNN+LSTM model for land use land cover maps generation.

Xu *et. al.*, [15] describes the highlights potential of deep learning that including CNNs, for remote sensing and satellite image classification detail for the images used in neural network. Chen *et. al.*, [16] demonstrates that the effectiveness of CNNs in satellite image classification, and achieving high accuracy.

A deep learning technique, convolutional neural network [33–35], quickly and efficiently extracts features from big data sets. The feature is extracted from layer to layer. The input layer, convolutional layer, pooling layer, fully connected layer, and output layer are the layers that comprise up CNN [37].

LeCun *et. al.*, [41] and Hinton *et. al.*, [42] laid the foundation of CNNs, which have been widely adopted for satellite image classification due to their ability to automatically learn hierarchical features. **Plaza *et. al.*, [43] and Mountrakiset. al.,[44]** discuss the challenges and techniques for classification using multispectral and hyper-spectral data acquired from satellites.

CNN is most powerful model in terms of efficiency and accuracy with image dataset via Transfer Learning [45]. There is a possibility to combining a CNN with a Long-Short Term Memory (LSTM), for better results and efficiency.

Convolutional Neural Network is also being used for automatic classification of the images with accuracy of 98 % [26]. However, it is require classifying the images and colored images of large size which is very useful for image segmentation process.

For assessing the accuracy of soft classification output mixed pixels has been incorporated attesting phase. Recently, the perception of fuzzy error matrix (FERM) has been used to assess the accuracy of soft classification [4].

The accuracy can also be measured by Kappa statistics [38]. This statistic indicates the proportion of chance agreement vs. real agreement that accounts for the percentage correct values of an error matrix. [29–31]. But these measures are employed to determine the results of hard classification. Because sub-pixel class boundaries exist, these measurements scarcely reflect the true quality of the identified image. [36] illustrates the requirement for accuracy evaluation of sub-pixel categorized images. There is currently no standard assessment method for evaluating the accuracy of soft categorization outputs [32].

The comparison table of some of the image classification method with data set, approach used and accuracy is shown below:

Table 1
Comparison table of Various Approaches of Satellite Image Classification

S. No.	Reference	Author's Name	Year	Data Set	Approach	Accuracy
1	[17]	Wilson et. al.,	2017	Crop Data	Alex-Net	90.50%
2	[18]	Davis et. al.,	2018	Sentinel-2 Images	Custom CNN	91.00%
3	[19]	Wilson et. al.,	2018	Crop Data	CNN-LSTM with Attention	88.80%
4	[20]	Johnson et. al.,	2019	Satellite Images	VGG-16	88.20%
5	[21]	(Davis et. al.,	2019	Satellite Time Series	Convolutional LSTM	90.30%
6	[22]	Smith et. al.,	2020	Land Cover Data	ResNet-50	94.30%
7	[23]	Smith et. al.,	2021	Satellite Images	CNN followed by LSTM	91.50%
8	[24]	White et. al.,	2022	Land Cover Data	DenseNet	93.70%
9	[25]	Brown et. al.,	2022	Remote Sensing Data	Stacked CNN+LSTM	89.70%
10	[26]	Ramprasath et. al.,	2018	Image Data	CNN	98.00%
11	[27]	Vittorio Mazzia et. al.,	2019	Sentinel-2 Images	R-CNN	96.50%
12	[28]	M. Kiani.	2020	Crop Data	CNN	98.01%

Methodology

Classification of satellite imagery is a very complex process due to many factors like pre-processing, training samples [52]. The main steps of classification of satellite imagery may include image preprocessing, feature extraction, training samples, classification approaches used, post classification processing and accuracy assessment. Figure 1 show the clear mythology used in classification of satellite imagery and accuracy assessment.

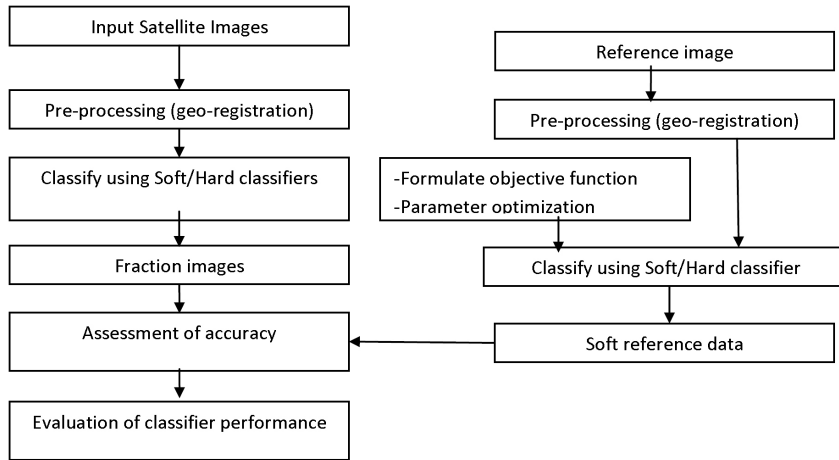


Figure 1

Brief methodology used in the classification and accuracy assessment

Requirement of the tool

Currently many commercial tools are available to analysis digital images. These tools offering various services like image enhancement, revelation, image conversion, segmentation classification, and accuracy. Some of these commercial tools are ENVI, e-Cognition, Idrisi, ER-Mapper, Erdas Imagine.

Beside this, SCMAP- “Soft classification methods and accuracy assessment package” developed by *Azizet. al., [46]* and SMIC- “Sub-pixel multispectral image classifier” created by *Kumar et. al., [47]* used various statistical learning algorithms for classification and FERM is used for accuracy assessment. Some tools are available based on fuzzy-image-classifier with and without noise. *Kumar et. al., [47]* also focused on Support Vector Machine. All these tools have limited features and not provided the solution of hybrid modes.

In this section 1st we elaborate CNN and LSTM models to classify satellite imagery. Subsequently we introduced a proposed hybrid CNN-LSTM model (tool/ framework). This tool provides classification and accuracy assistant based on hybrid CNN-LSTM.

A. CNN

When classifying satellite images, CNN is used to identify objects in the image, such as water bodies, dense forest, highways, rivers, urban

areas, and buildings, in order to extract features from the image input data. Due to their ability to learn immediately from incoming data, CNN is most pertinent [50-52]. The general overview of working of CNN is shown in the following Figure 2:

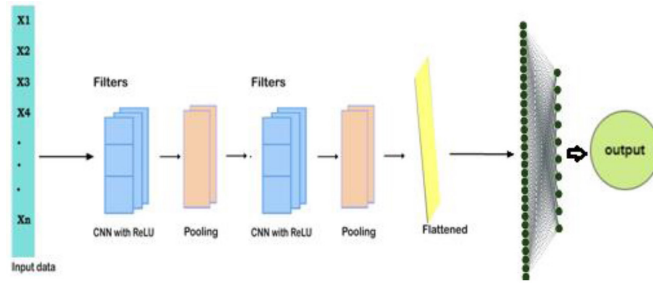


Figure 2
CNN Architecture

CNN model is built up with Convolutional layers used to extract features from image input data with the support of filters after performing convolution operation on input data. Activation function used is rectified linear unit (ReLU). After that pooling layers are used to down-sampled the feature maps of convolution layers. The output of pooling layers are flattened in 1D vector and finally output layer use a proper activation function (Softmax) to generate class [50-52].

B. LSTM

Figure 3 shows the brief architecture of LSTM neural network. LSTM, a recurrent neural network (RNN) is used to resolve the issues of vanishing gradient problem to learn patterns from sequential data. Each LSTM add

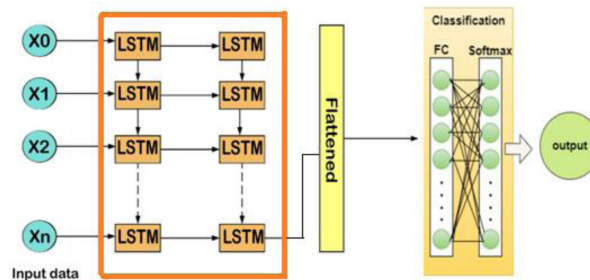


Figure 3
Architecture of LSTM Neural Network

and remove information to the cell's state and has 3 gates named input, forget and output gates. C_t depicts the internal state of an LSTM cell at time stamp t . It compiles data from older time stamp and serves as the cell's memory [50-52].

Three main components and LSTM cell's internal state are:

- i. Internal State: C_t indicates the internal state of an LSTM cell at the moment t . It accumulates data from former stages of time and represents the cell's memory. Combining addition and element-wise multiplication updates the internal state
- ii. Input Gate: How much newly acquired information should be incorporated into the internal state is decided by the input gate. It produces values between zero and one.

$$i_t = \partial(W_{xi} * x_t + W_{hi} * h_{t-1} + b_i) \quad (1)$$

Here, i_t = The Input Gate; h_{t-1} = Previous Hidden State; x_t = Current Input

- iii. Forget Gate: Forget Gate controls the amount of content that should be wiped from the internal state. It produces values between zero and one.

$$f_t = \partial(W_{xf} * x_t + W_{hf} * h_{t-1} + b_f) \quad (2)$$

- iv. Update: The update, $\tilde{C}_t$, reflects the newly-added potential values to the internal state and specified by:

$$\tilde{C}_t = \tanh(W_{xc} * x_t + W_{hc} * h_{t-1} + b_c) \quad (3)$$

- v. Final Internal State: Final internal state, C_t , can be defined as:

$$C_t = f_t C_{t-1} + i_t \tilde{C}_t \quad (4)$$

Where, C_{t-1} = old internal state

- vi. Output Gate: This gate determines the amount of data received from the internal state and produces a value between 0 and 1. It is calculated as follows:

$$o_t = \partial(W_{xo} * x_t + W_{ho} * h_{t-1} + b_o) \quad (5)$$

- vii. Hidden State: The hidden state h_t represents the cell's output at time step t and is calculated as follows:

$$h_t = o_t * \tanh(C_t) \quad (6)$$

These equations describe the LSTM cell's operations where weight matrices (W) and bias vectors (b) are learning parameters that are optimized during the training process [50-52].

C. Proposed model: Hybrid CNN-LSTM

This model is a hybridization of CNN and LSTM and the steps of this model is categorized in two parts which is already described in Section-A and Section-B for CNN and LSTM models respectively [50-51]. Figure 4 shows the brief architecture of the CNN-LSTM hybrid model: -

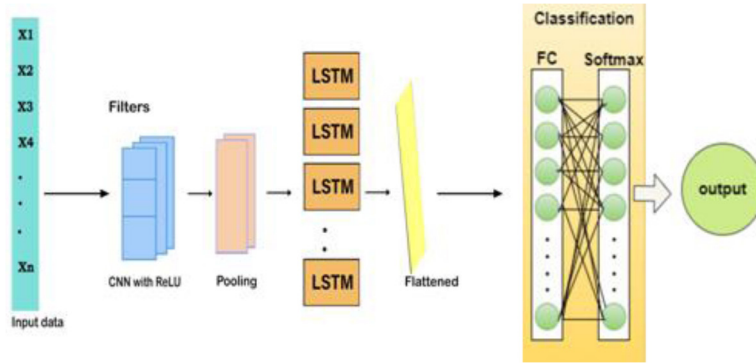


Figure 4

Proposed Architecture of CNN-LSTM Hybrid model

Experiments and Results

This section covers the study area and data set along with the experimental results after optimization of various parameters used in proposed hybrid model CNN-LSTM with classified outputs. Comparative study of accuracy assessment with CNN and LSTM is also described in this research paper.

A. Study Area and Data Set used:

In this research, we study the Haridwar city in state of Uttarakhand, India surrounding by the regions Dehradun, Pauri-Garhwal, Muzaffarnagar and Bijnor in North-East, East, South and West respectively [52]. Landsat-8 and Formosat-2 satellite data is used for various land cover classes, including RR sand, wheat, water bodies, dense forest, grassland, and eucalyptus. Figure 5 showing the study area of Haridwar region.

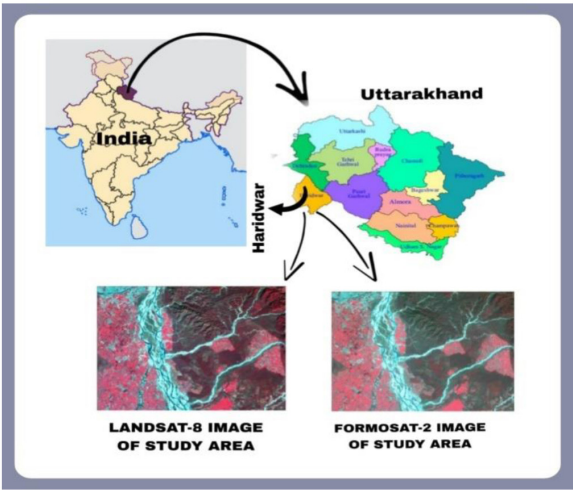


Figure 5
Study Area of Haridwar Region

Landsat-8 and formosat-2 satellite’s sensor specifications are shown in the following Table 2 and Table 3 respectively with bandwidth and resolutions.

Table 2
LANDSAT 8 Bands Specifications [48]

Sensor Used	Band	Band-Name	Wavelength (in μm)	Resolution
O.L.I	Band-1	Coastal-Band	From 0.43 to 0.45	30 Meter
O.L.I	Band-2	Blue-Band	From 0.45 to 0.51	30 Meter
O.L.I	Band-3	Green-Band	From 0.53 to 0.59	30 Meter
O.L.I	Band-4	Red-Band	From 0.63 to 0.67	30 Meter
O.L.I	Band-5	NIR-Band	From 0.85 to 0.88	30 Meter

Table 3
FORMOSAT-2 Bands Specifications [49]

Spectral Bands	Bands	Wave Lengths (μm)	Resolution (m)	Sensor type
1 PAN (Panchromatic band)	1	0.45 - 0.90	2	Electro-optical

Contd...

4 MS (Multispectral bands)	B1(Blue)	0.45 - 0.52	8	Electro-optical
	B2(Green)	0.52 - 0.60	8	Electro-optical
	B3(Red)	0.63 - 0.69	8	Electro-optical
	B4(NIR)	0.76 - 0.90	8	Electro-optical

B. Implementation Setup

We have used Python 3 using Jupyter Notebook to develop a proposed hybrid model and employed Gdal, Keras and Tensorflow packages. For more computing power we use 4GB NVIDIA-GPU and use Google-Colab with a RAM of 100GB to conduct our all required experiments [50-52].

In this paper, we optimize the various parameters to increase the accuracy of satellite images. To ignore over-fitting, we divide the data set into three parts namely training, testing and validating set respectively [15-21]. Total 75% data is used for training, 15% is used for testing and remaining 10% data is used for validating the data.

Hybrid CNN-LSTM model, which begins with CNN layers and is followed by LSTM layer, is aimed to extract the various features. The filter size is 3X3 and max-pooling is used to reduce the image dimension. Adam optimizer is used to reduce cross-entropy and dropout rate is 0.40 to reduce over-fitting. The Learning rate of parameters is 0.001 and model is trained with batch of size 30 and epoch 50 [50-52].

The parameters used in effective learning of model are revealed in the Table 4:

Table 4
Parameters of Proposed Hybrid CNN-LSTM Model

S. No.	Parameters
1	Number of CNN Layers
2	Filter Size, Kernel Size
3	Max-Pooling
4	Epochs
5	Batch Size
6	Dropout Rate
7	Loss Function
8	Optimizer
9	LSTM Units

The performance of models to classify satellite imagery can be accessed through certain standard metrics as shown in the Table 5:

Table 5
Performance Metrics for Satellite Image Classification

Performance Metrics	Formula/Equation
Recall	$TP / (TP + FN)$
Precision	$TP / (TP + FP)$
Accuracy	$(TP + TN) / (TP + TN + FP + FN)$
F1-Score	$2(Precision \times Recall) / (Precision + Recall)$
TP: True Positive; TN: True Negative;	
FP: False Positive; FN: False Negative	

Results

In this section we find the results of our data set of satellite images to classify various classes such as wheat, water bodies, dense forest, grassland, RRsand and eucalyptus using the proposed Hybrid CNN_LSTM model. Also evaluate the performance of our model in terms of overall accuracy. First we use the Hybrid CNN-LSTM model to classify all classes and find the accuracy of each class and then we compare this model with CNN and LSTM results of our data set.

The following Figure 6 describes the comparison between Hybrid CNN-LSTM accuracy with CNN and LSTM of our data set.

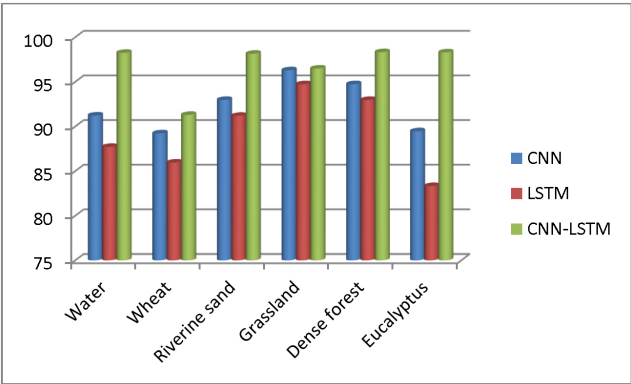


Figure 6
Analysis with Proposed Hybrid CNN-LSTM with CNN and LSTM

The mean overall accuracy of all classes in performance evaluation of Hybrid CNN-LSTM is 96.80% while LSTM has 89.32% and CNN has 92.33%. Further Kappa statistics from the confusion matrix for the trained model on the data set is also calculated and most of the test data was found to be accurately classified. The Kappa of Hybrid CNN-LSTM, LSTM and CNN are 96.16, 87.19 and 90.79 respectively. Figure 7 showing the performance evaluation of Hybrid CNN-LSTM with CNN and LSTM.

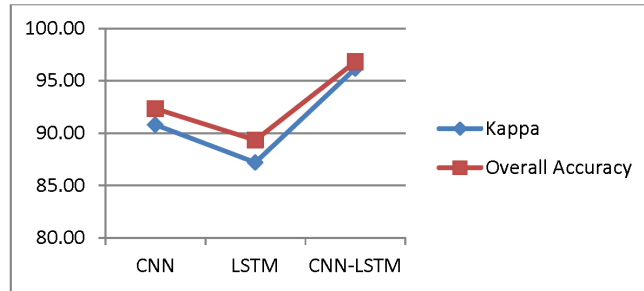


Figure 7

Performance Evaluation of Hybrid CNN-LSTM with CNN and LSTM

After analysis of these findings, we infer that our suggested model achieves significantly higher accuracy.

Figure 8(a) and Figure 8(b) are clearly indicated that the training and validation curves both remain in the right direction. The accuracy of the model increases gradually and moves towards a higher accuracy, while loss is reduced and advances towards zero. This indicates the model's quality as the gap is very low between two curves.

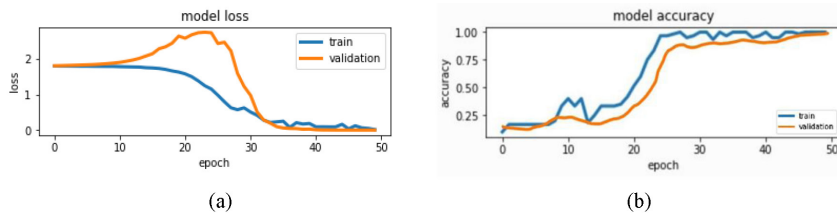


Figure 8

Loss and Accuracy during training and validation

In an experiment, we evaluated our trained model on the satellite data of Landsat-8 and Formosat-2. Figure 9 displays the classified outputs.

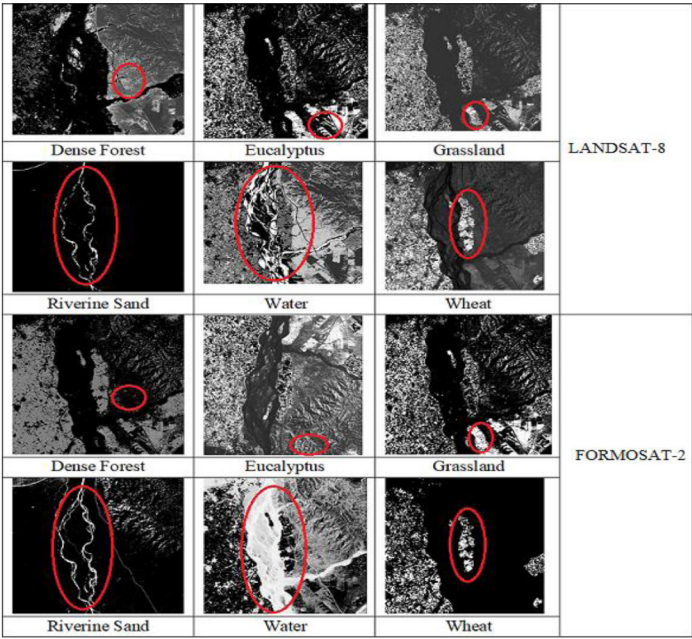


Figure 9
Classified outputs-Landsat-8 and Formosat-2

Conclusion

In this research, the outcome is generated from Landsat-8 and Formosat-2 image data. The neural network CNN, LSTM and Hybrid CNN-LSTM are widely used models in the classification of satellite imagery. However, these methods need a large amount of satellite data and collection of images is a time consuming process. This paper introduced a Hybrid CNN-LSTM method for classifying remote sensing satellite images for various land cover classes with accuracy assessment with optimization of various parameters. The experimental results of our model prove that our approach is much accurate as compare to other approaches.

However, it is necessary to identify limitations in classification and accuracy assessment. The training time of the model is time consuming and need lot of time to complete.

In future, we plan to apply Genetic algorithms with Neural Networks while focusing of the various challenges in network complexity, processing time and accuracy.

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