

CNNs FOR MULTI-SPECTRAL SATELLITE IMAGE CLASSIFICATION

GUIDE : PROF SARITH DIVAKAR M (CSE & IT DEPARTMENT)

PRESENTED BY
SUBITH O U
S7 CSEB 32
KSD18CS084

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INTRODUCTION

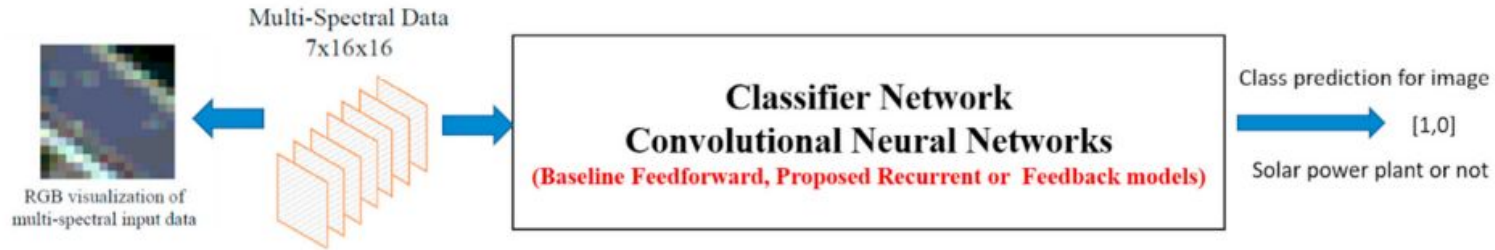
- In the multi-spectral satellite image classification we are using feed-forward, Recurrent and feedback CNNs.
- We compare the accuracy of feed-forward, recurrent and feedback CNNs on multi-spectral satellite image classification by using the Intersection over Union (IoU) evaluation metric.
- For analysis, we use these techniques for the classification of solar power plants.

EXISTING vs PROPOSED

- In the existing system, the baseline CNN model is used for classification.
- But in the proposed system is using the recurrent and feedback CNN.
- Based on the performance analysis, the proposed system is outperforming the baseline CNN.

SOLAR POWER PLANT CLASSIFICATION

- In the solar power plant classification, we using feed-forward, recurrent, and feed-back CNNs.



DATASET

- We use the MUltiband Satellite Imagery for object Classification (MUSIC) to detect Photovoltaic Power Plants (MUSIC4P3) dataset.
- This dataset consists of multi-spectral satellite images captured by Landsat 8 and their respective solar power plant labels for each scene.
- Landsat 8 provides visual data of the Earth from 11 bands of different wavelengths and spatial resolutions obtained from two sensors since 2013.
 - Operational Land Imager (OLI)
 - Thermal Infrared Sensor (TIRS)

DATASET

- Overview of the MUSIC4P3 dataset used in this work.

Table 1. Observation wavelength and spatial resolution of Landsat 8 imaging sensors.

Sensor	Band	Wavelength (μm)	Resolution(m/p)
OLI	1	0.43 – 0.45	30
	2 (B)	0.45 – 0.51	30
	3 (G)	0.53 – 0.59	30
	4 (R)	0.64 – 0.67	30
	5	0.85 – 0.88	30
	6	1.57 – 1.65	30
	7	2.11 – 2.29	30
	8	0.53 – 0.68	15
	9	1.36 – 1.38	30
TIRS	10	10.60 – 11.19	100
	11	11.50 – 12.51	100

- **Training data:** Positive Samples are 4,851 and Negative Samples are 320,000.
- **Validation data:** Positive Samples are 21 and Negative Samples are 160,533.
- **Test data:** Positive Samples are 105 and Negative Samples are 820,666.

FEED-FORWARD CNN (INet) FOR MULTI-SPECTRAL IMAGE CLASSIFICATION



Figure 2 INet Model: Feed-forward baseline CNN for solar power plan classification on multi-spectral satellite imagery

FEED-FORWARD CNN (INet) FOR MULTI-SPECTRAL IMAGE CLASSIFICATION

$$\mathbf{F1} = \zeta \left(\left(\mathbf{w}_{conv1}^{forward} \right) * \mathbf{U} \right)$$

$$\mathbf{F2} = \zeta \left(\left(\mathbf{w}_{conv2}^{forward} \right) * \mathbf{F1} \right)$$

$$\mathbf{F3} = \zeta \left(\left(\mathbf{w}_{conv3}^{forward} \right) * \mathbf{F2} \right)$$

where \mathbf{U} is the input multi-spectral image.

$\mathbf{W}^{forward}$ is the weights for the convolutional filters for forward processes at each layer.

$\mathbf{F1}$, $\mathbf{F2}$ and $\mathbf{F3}$ are CNN feature representations.

RECURRENT CNN (R-Net) FOR MULTI-SPECTRAL IMAGE CLASSIFICATION



Figure 3 Proposed Recurrent CNN as an extension to baseline feed-forward CNN INet for solar power plan classification

RECURRENT CNN (R-Net) FOR MULTI-SPECTRAL IMAGE CLASSIFICATION

$$\mathbf{F1}_t = \zeta \left(\left(\mathbf{w}_{conv1}^{forward} \right) * \mathbf{U}_t \right)$$

$$\mathbf{F2}_t = \zeta \left(\left(\mathbf{w}_{conv2}^{forward} \right) * \mathbf{F1}_t + \left(\mathbf{w}_{conv2}^{recurrent} \right) * \mathbf{F2}_{t-1} \right)$$

$$\mathbf{F3}_t = \zeta \left(\left(\mathbf{w}_{conv3}^{forward} \right) * \mathbf{F2}_t + \left(\mathbf{w}_{conv3}^{recurrent} \right) * \mathbf{F3}_{t-1} \right)$$

Where \mathbf{U} is the input multi-spectral image.

$\mathbf{W}^{forward}$ & $\mathbf{W}^{recurrent}$ weights are the convolutional filters used for feed-forward and recurrent inputs at each time step, t , respectively.

$\mathbf{F1}$, $\mathbf{F2}$ and $\mathbf{F3}$ are CNN feature representations.

t is the time step.

FEEDBACK-CNN (F-Net) FOR MULTI-SPECTRAL IMAGE CLASSIFICATION

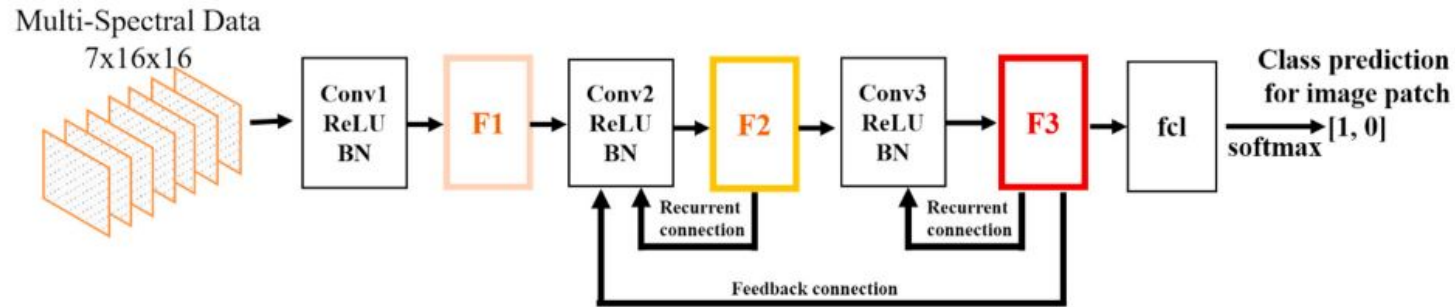


Figure 4 Proposed Feedback-Recurrent CNN as an extension to Recurrent CNN based on INet for solar power plant classification

FEEDBACK-CNN (F-Net) FOR MULTI-SPECTRAL IMAGE CLASSIFICATION

$$\mathbf{F1}_t = \zeta \left(\left(\mathbf{w}_{conv1}^{forward} \right) * \mathbf{U}_t \right)$$

$$\mathbf{F2}_t = \zeta \left(\left(\mathbf{w}_{conv2}^{forward} \right) * \mathbf{F1}_t + \left(\mathbf{w}_{conv2}^{recurrent} \right) * \mathbf{F2}_{t-1} + \left(\mathbf{w}_{conv2}^{feedback} \right) * \mathbf{F3}_{t-1} \right)$$

$$\mathbf{F3}_t = \zeta \left(\left(\mathbf{w}_{conv3}^{forward} \right) * \mathbf{F2}_t + \left(\mathbf{w}_{conv3}^{recurrent} \right) * \mathbf{F3}_{t-1} \right)$$

Where \mathbf{U} is the input multi-spectral image.

$\mathbf{W}^{forward}$ & $\mathbf{W}^{recurrent}$ weights are the convolutional filters used for feed-forward and recurrent inputs at each time step, t , respectively.

$\mathbf{F1}$, $\mathbf{F2}$ and $\mathbf{F3}$ are CNN feature representations.

t is the time step.

TRAINING PROCEDURE

- All models trained on similar settings by using a dataset of 16×16 -pixel image patches with corresponding annotations using cross-entropy loss.
- For optimization of the model parameters, SGD (Stochastic Gradient Descent) with fixed learning rate of 0.01 and momentum of 0.9 is selected.
- Comparison after train the models with 1000 iterations.

EXPERIMENTAL RESULTS

- For the performance evaluation, we use the Intersection over Union (IoU) metric.
- $\text{IoU} = \text{True Positive} / (\text{True Positive} + \text{False Negative} + \text{False Positive})$

INet* [2,3]	INet [2, 3]	R-Net	F-Net
0.52	0.36	0.38	0.55

Evaluation results of the compared models based on Intersection over Union (IoU)

CONCLUSION

- Using top-down signals (especially recurrent and feedback features together) on CNNs can provide good representation of multi-spectral images which can in turn improve classification accuracy drastically.

REFERENCES

- Exploring Recurrent and Feedback CNNs for Multi-Spectral Satellite Image Classification - ScienceDirect
- Sci-Hub | Detection by classification of buildings in multispectral satellite imagery. 2016 23rd International Conference on Pattern Recognition (ICPR) | 10.1109/ICPR.2016.7900150

THANK YOU