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4D Convolutional Neural Networks for Multi-Spectral and Multi-Temporal Remote Sensing Data Classification

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Motivation

- Multi-Spectral (MS) & Multi-Temporal (MT) imaging
- **High-dimensional data**, time-series
  - Capture multi-dimensional dependencies & correlations
  - Extend current CNN architectures
- Remote Sensing (RS) data classification
  - Semantic segmentation
  - Land-cover classification, flood detection
  - Physical characteristics monitoring

Contributions

- Introduction of 4D-CNNs for MT-RS land-cover classification
- Effective exploitation of higher-order correlations without any information loss
- End-to-end learning of spatio-spectro-temporal features at the same time
- Demonstration of the 4D-CNN superiority over lower-dimensional CNNs and state-of-the-art methods

Proposed Method-Stacked Convolution

- Main objective**:** Perform 4D convolution
- How: Stacking multiple sequences of 3D convolutions along the last dimension

$$y_{k,l,m,n} = f\left(\sum_{c}^{C_{in}}\sum_{s=0}^{S-1}\sum_{t=0}^{T-1}\sum_{i=0}^{H-1}\sum_{j=0}^{W-1} w_{i,j,t,s}x_{c,(k+i)(l+j)(m+t)(n+s)} + b_{i,j,t,s}\right)$$

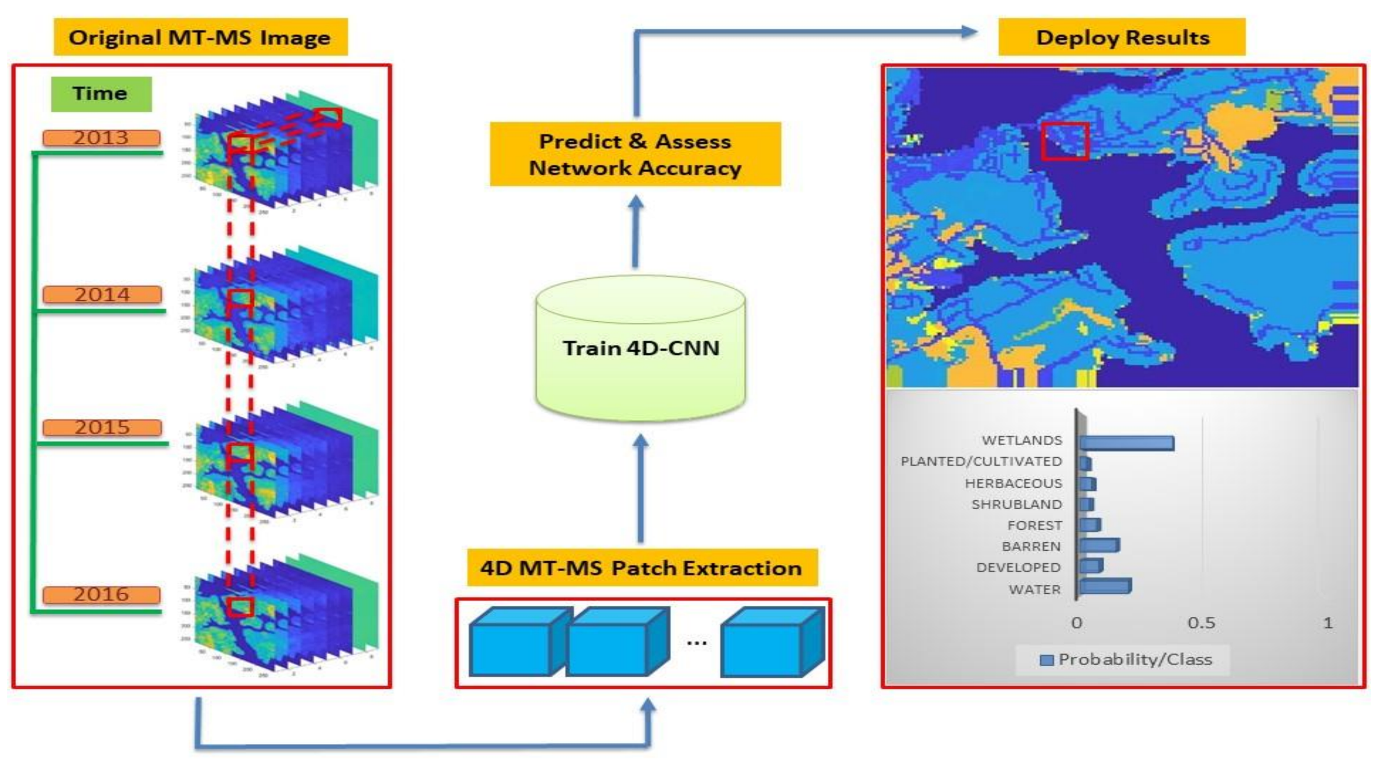
$$= f\left(\sum_{s=0}^{S-1}\left[\sum_{c}^{C_{in}}\sum_{t=0}^{T-1}\sum_{i=0}^{H-1}\sum_{j=0}^{W-1} w_{i,j,t,s}x_{c,(k+i)(l+j)(m+t)(n+s)}\right] + b_{i,j,t,s}\right)$$

$$= f\left(\sum_{s=0}^{S-1} C_{3D} + b_{i,j,t,s}\right)$$

- Why going stacked: **Fast** GPU-based **implementation**, using **Tensorflow** primitives
- **Is it feasible?** Yes
  - Convolution: Linear operation → Summation order can change
  - Implementation: Further re-arrangement of sums' indices → Not separable convolution
- Also applied in semantic segmentation and video classification tasks

4D-CNN for MT-RS Land-Cover Classification

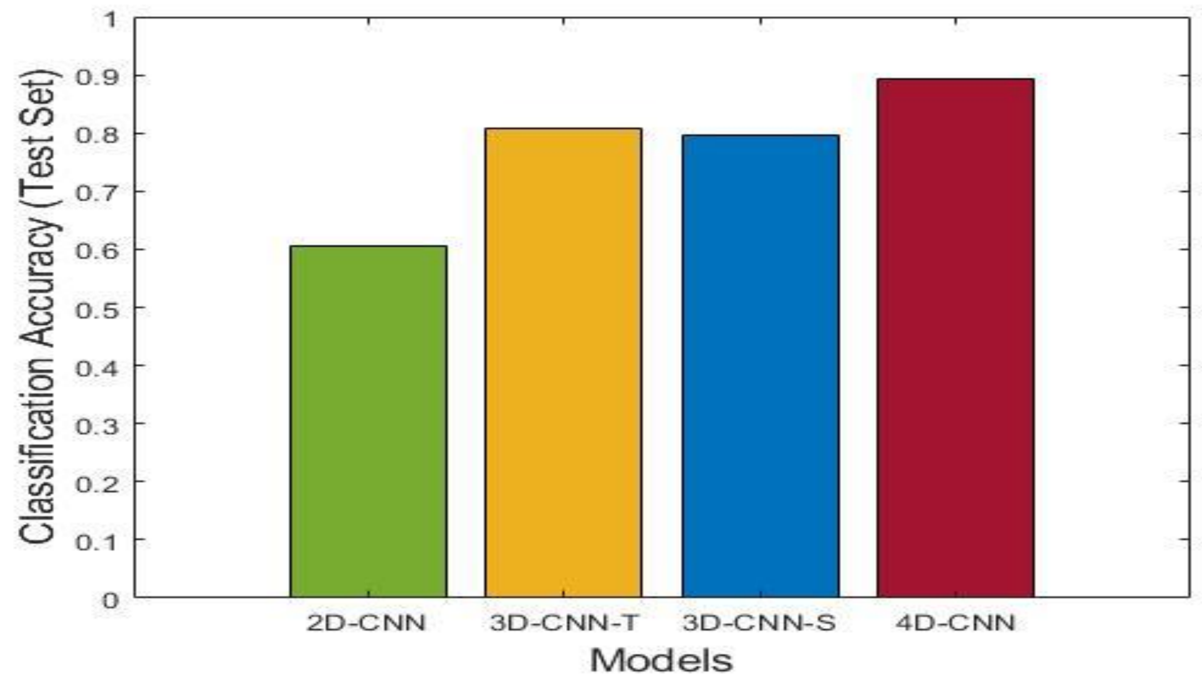
- Training samples: Overlapping 4D patches around each pixel of raw MT-RS imagery

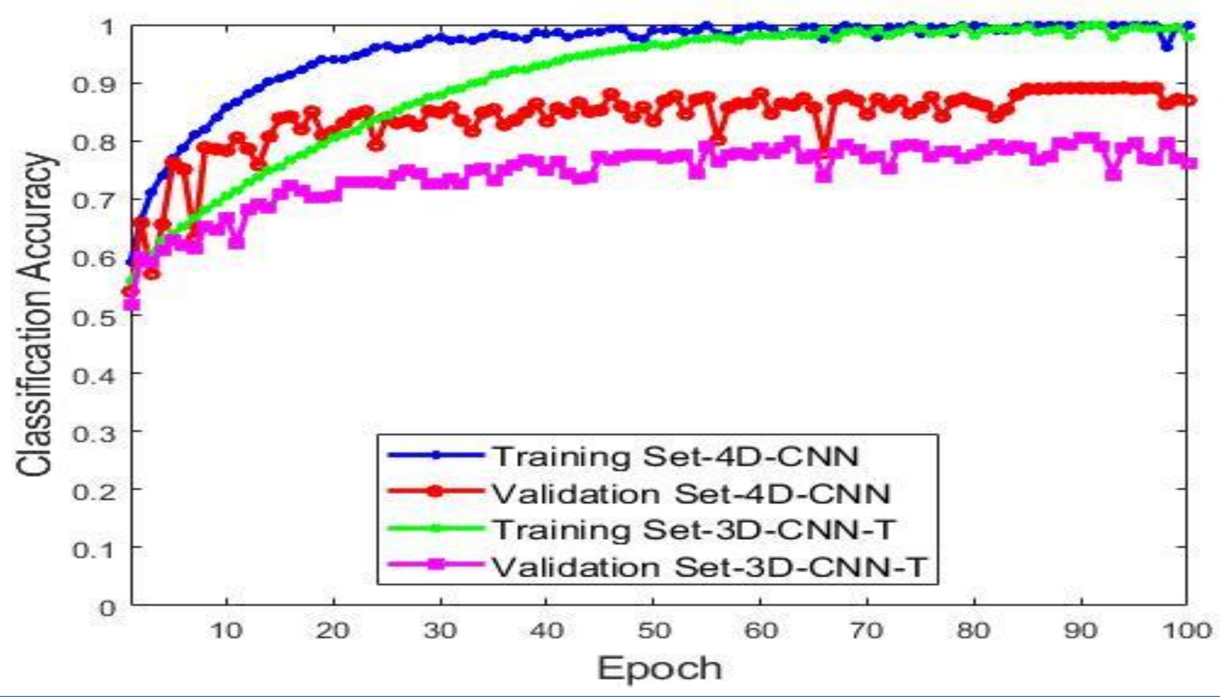


- **Model architecture:** Fully-Convolutional (FC) network
  - No need for considering scaling/translation factors
  - FC networks perform remarkably in similar tasks (e.g. Hyper-Spectral pixel-level classification)
- Model topology
  - Stacks of (Conv-BN-ReLU) layers
  - Kernel size equal to 3 across every dimension, "same" padding
  - Loss-function: Categorical cross-entropy, Optimizer: Adam
  - Batch-size=128, Epochs: 100

4D-CNN Parameter Tuning

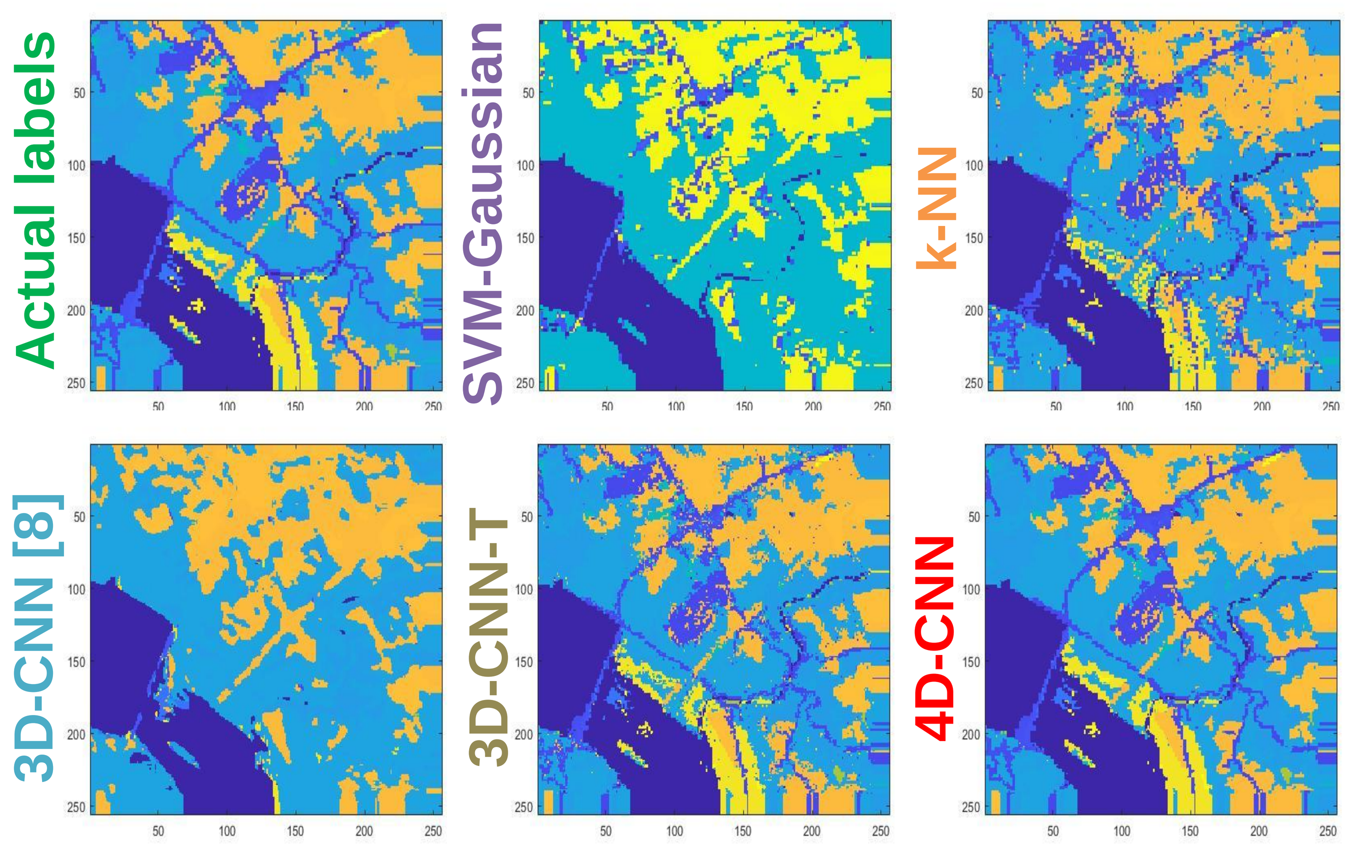
- Input data dimensionality impact
  - 2D-CNN: Exploit only spatial information
  - 3D-CNN-T: Exploit spatial & temporal information
  - 3D-CNN-S: Exploit spatial & spectral information
  - **4D-CNN**: Exploit spatial & spectral & temporal information
- **Hyper-parameter optimization**
  - #Stack-of-layers in each CNN architecture (i.e. 2, 3, 4)
  - Spatial patch-size of training samples (i.e. 5x5, 7x7)





Comparison to State-of-the-Art and Machine Learning Methods

Model	Accuracy	Time	F1-Score
k-NN	0.7443	0.000	0.5747
SVM-Gaussian	0.5945	2.006	0.4995
3D-CNN [8]	0.7097	6.003	0.5090
2D-CNN	0.6049	4.928	0.3624
3D-CNN-T	0.8080	14.558	0.6509
3D-CNN-S	0.7953	27.435	0.6552
4D-CNN	**0.8916**	**107.619**	**0.7796**



Experimental Setup

- Dataset Description: IEEE GRSS Data Fusion Contest dataset
  - Landsat-8 MS imagery (9 spectral bands), collected once a year (2013-2016)
  - USGS NLCD labels of 2016, 15 different land-cover classes (spatial resolution=30m)
  - 2250 different tiles over Maryland, USA
- **Pre-processing steps**
  - Selection of a tile with no undefined label values
  - Spatial padding & sub-sampling to create MT-RS imagery of spatial size 256x256
  - Spatial patch-extraction around each pixel, across all spectral bands & time-instances
  - Created data: 256x256=65536 samples, of size (p,p,9,4) each
  - Data-split: Training/Validation/Test → 60%/20%/20%, random
- Platforms
  - Software: Python-Tensorflow-Keras, Hardware: NVIDIA Quadro P4000 (8Gb RAM)

Conclusions

- **Efficient classification** of MT-RS data via 4D-CNNs
- **Clear improvements** over lower-dimensional CNNs, machine learning and state-of-the-art methods
- **Robustness** towards class-imbalance regimes

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