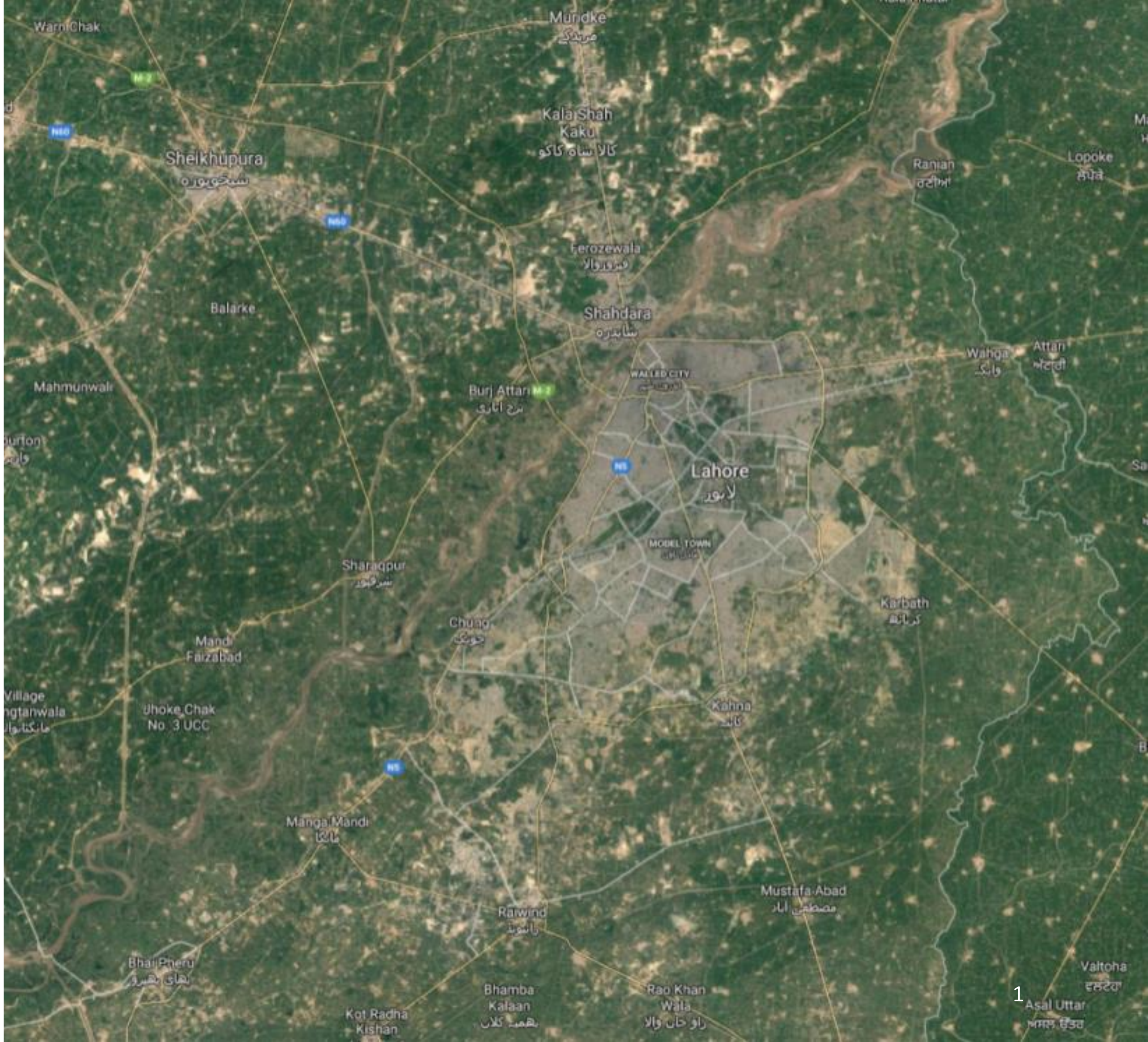
CV Lab
LUMS

Using 3D Residual Network For Spatio-Temporal Analysis Of Remote Sensing Data

Muhammad Ahmed Bhimra, Usman Nazir, Murtaza Taj

LUMS

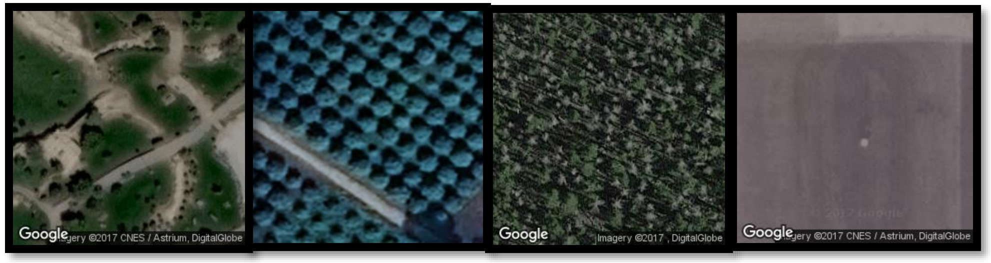


Agenda

- Challenges

- Proposed Network

- Dataset Annotation



Introduction

Construction

2011 2013 2017

Destruction

2011 2013 2017

Cultivation

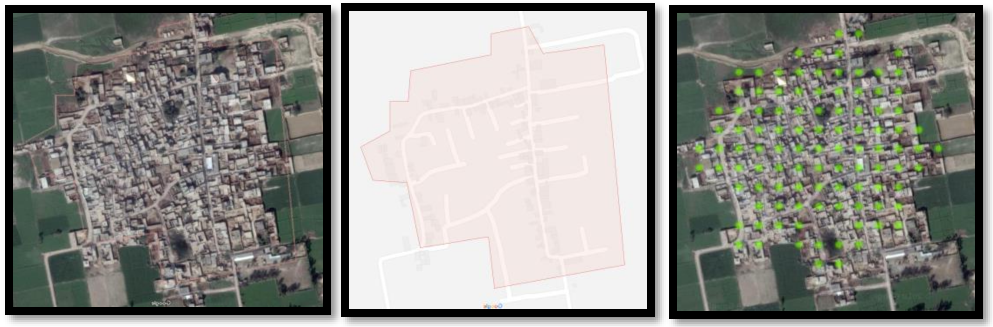
2011 2013 2017

Decultivation

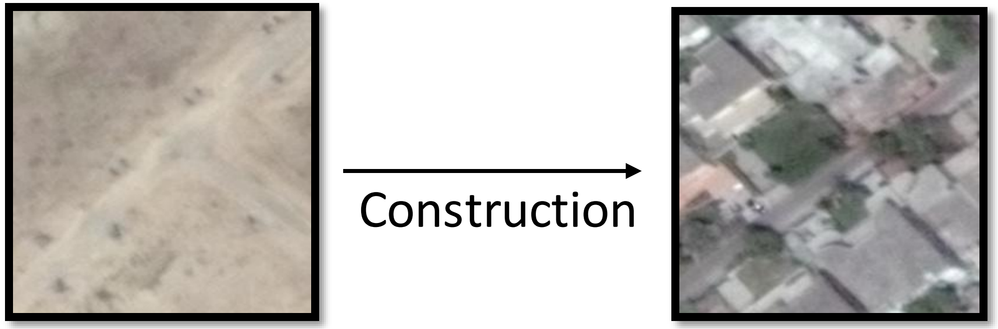
2011 2013 2017

Problem Statement

- Identification of spatio-temporal trends such as construction in satellite images

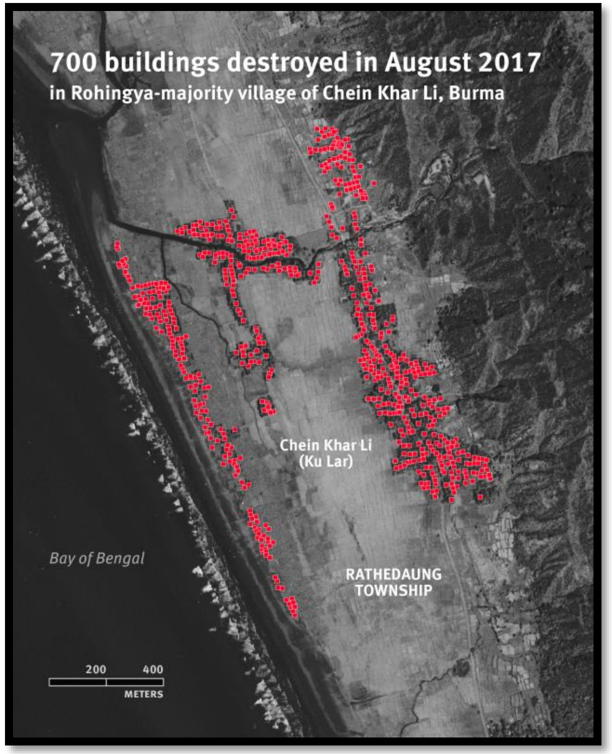


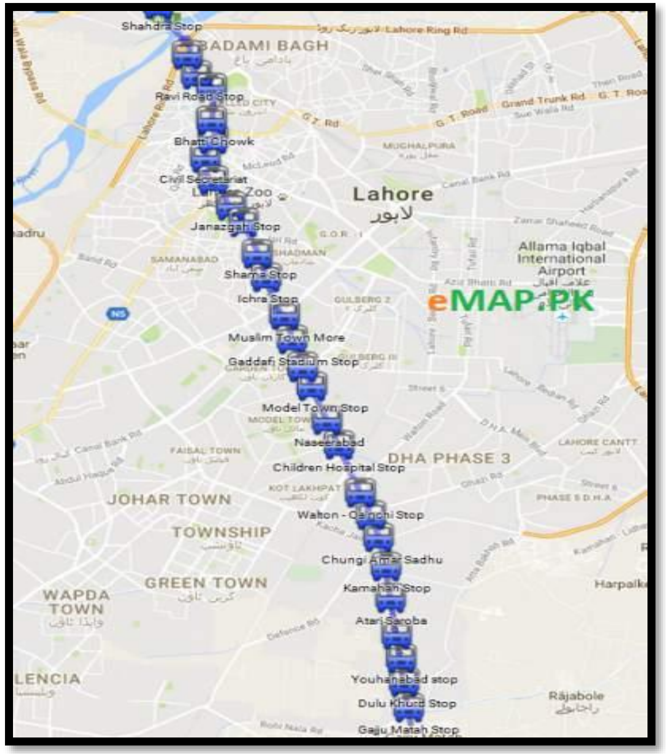
Spatial Problem: House Detection



Spatio-Temporal Problem

Motivation





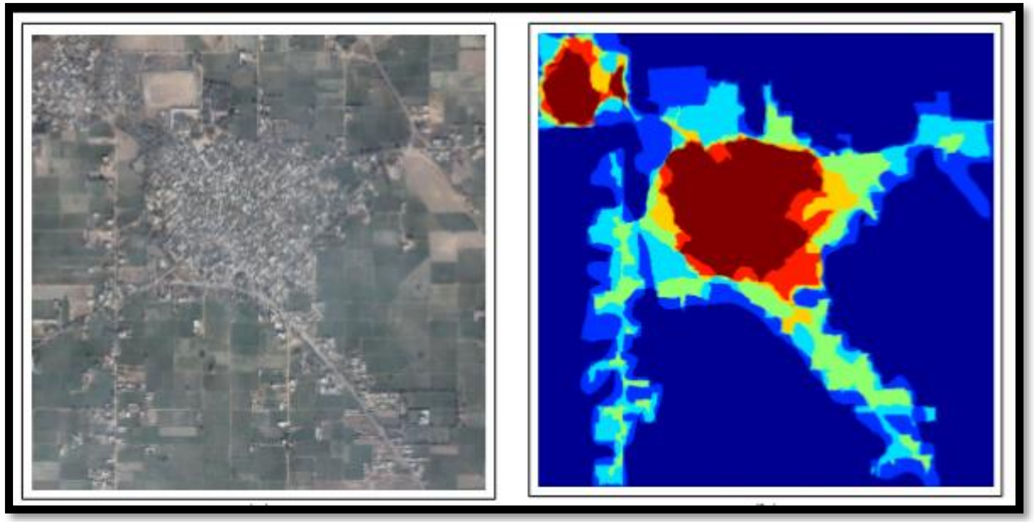
Macmanus, et al. "Genocide Achieved, Genocide Continues: Myanmar’s Annihilation of the Rohingya." *Genocide Achieved, Genocide Continues: Myanmar’s Annihilation of the Rohingya* (2018)

Related Work

- Village Finder
- Poverty Prediction
- Urban Damage Detection

Related Work

- Village Finder: Segmentation of Nucleated Villages in Satellite Imagery [Kashif Murtaza, et al. (2009)]

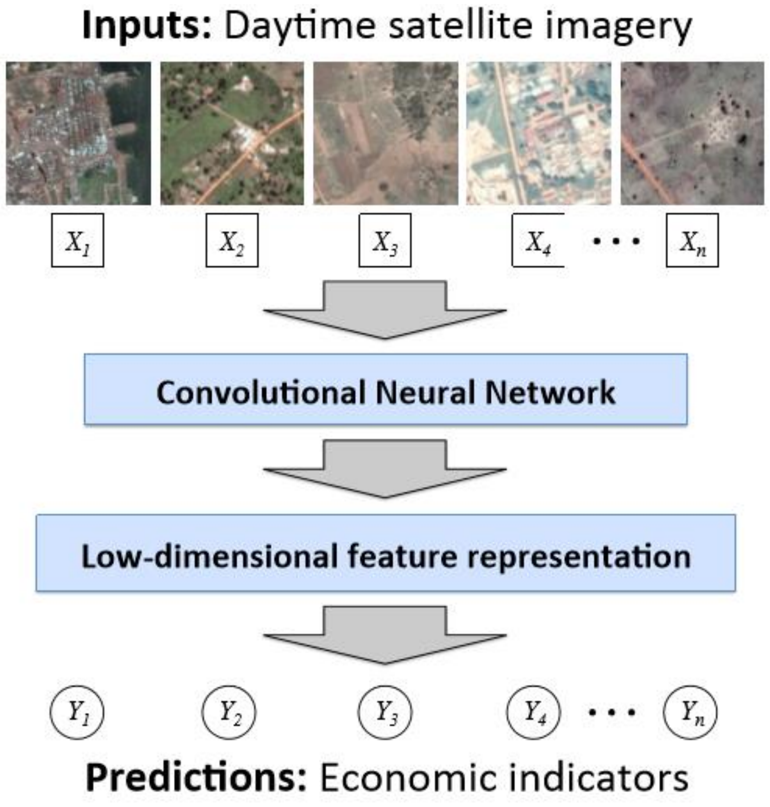


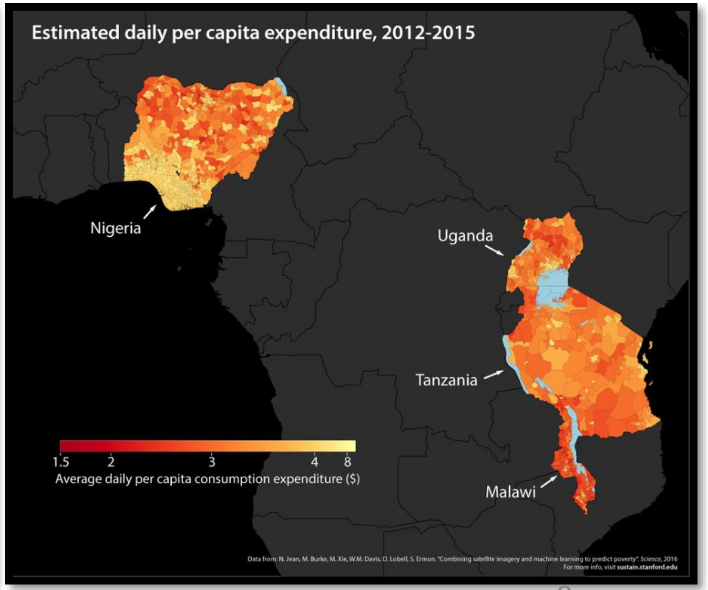
Google Earth Satellite Image

Annotations for the village border

Related Work

- Combining Satellite Imagery and Machine Learning to Predict Poverty [Jean, Neal, et al. (2016)]





Related Work

- Neural Network and Local Laplace Filter Methods Applied to very High Resolution Remote Sensing Imagery in Urban Damage Detection [Hordiiuk, D. M., et al. (2017)]

Buildings identified before and after disaster

Destroyed buildings predicted by CNN

Ground truth

Challenges

- Cloud Cover

- Intra Class Variation

Challenges

- Quality Variation

New York

Jerusalem

Lahore

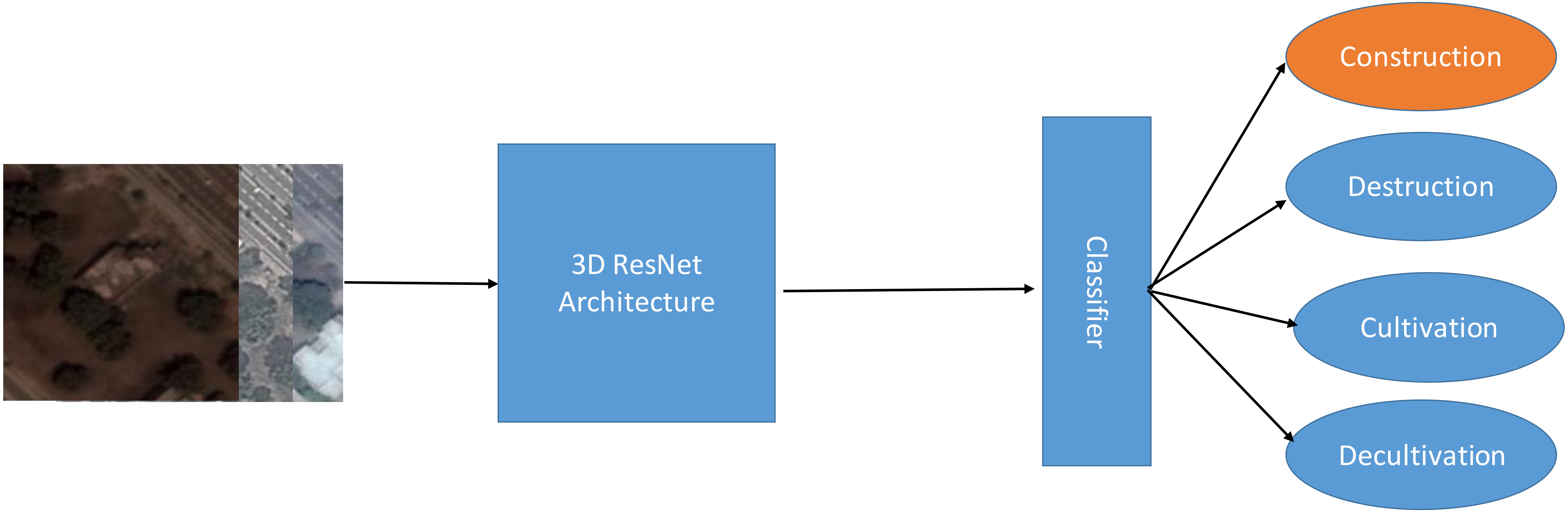
- Temporal Variations
  - Color Contrast

2011

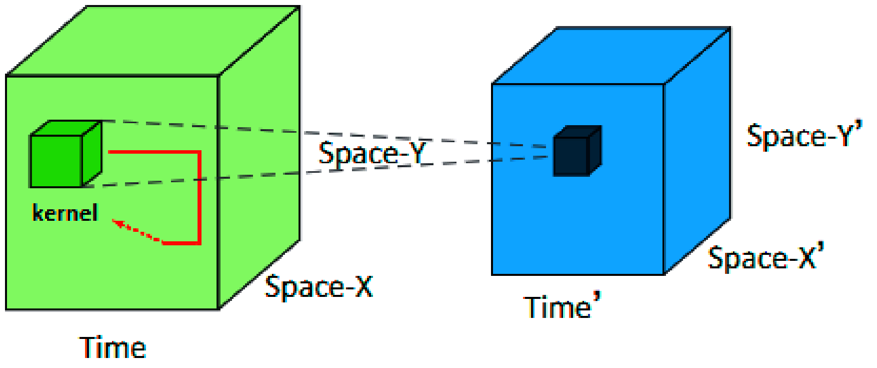
2013

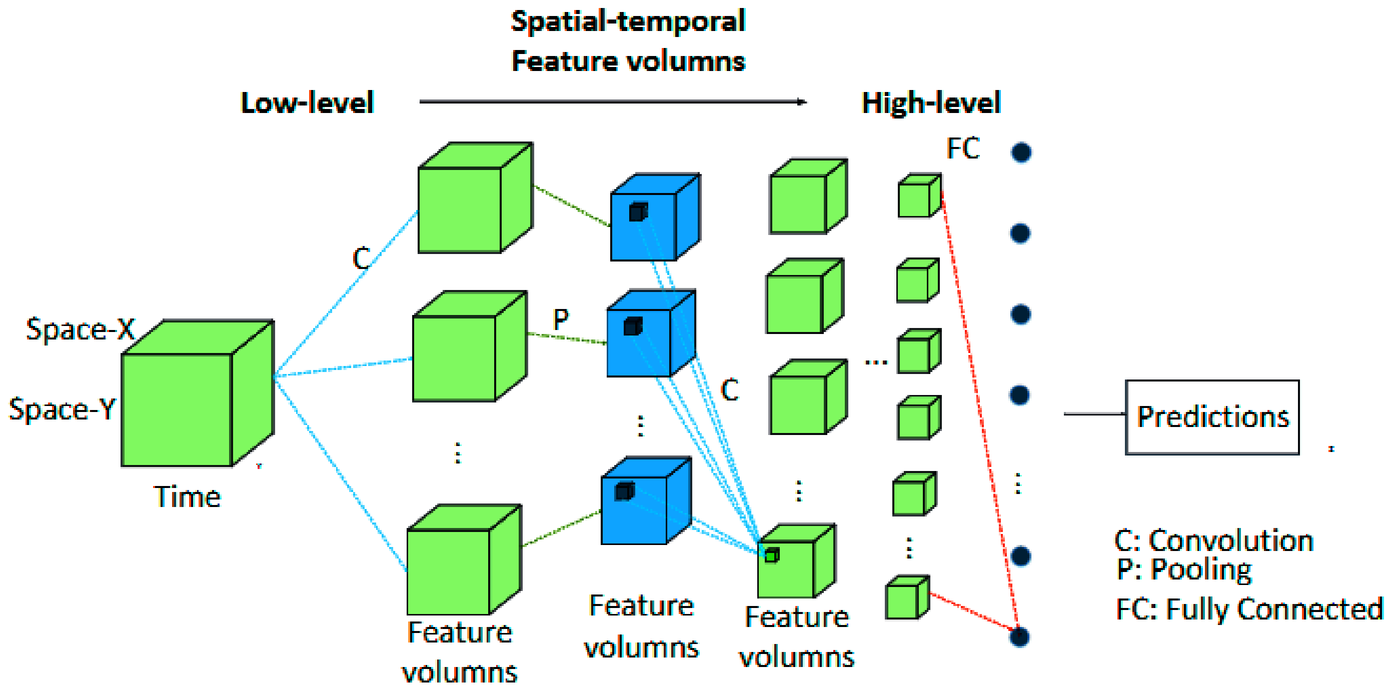
2017

Proposed Network Architecture



3D Convolution

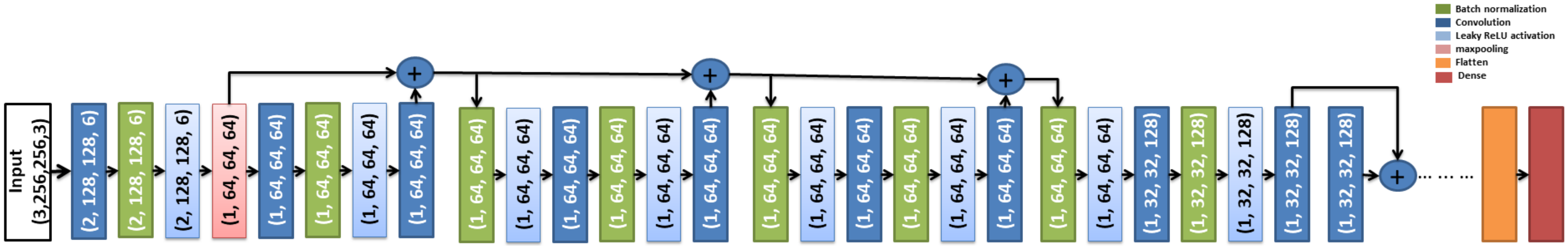




Chen, Cen, et al. "Exploiting Spatio-Temporal Correlations with Multiple 3D Convolutional Neural Networks for Citywide Vehicle Flow Prediction." *2018 IEEE International Conference on Data Mining (ICDM)*. IEEE, 2018

Proposed Model

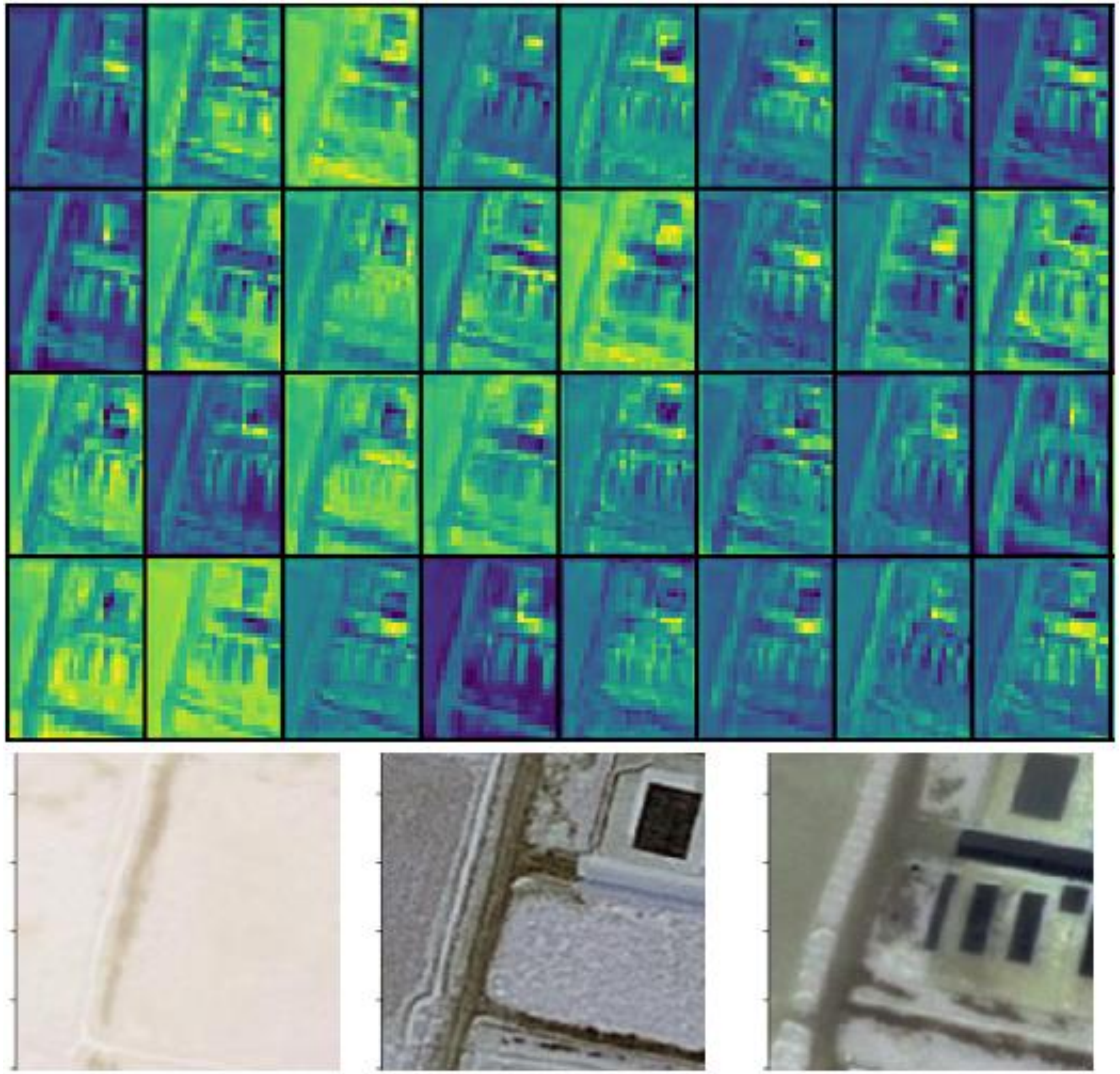
- 4D Input Tensor
- 3D convolution
- LeakyReLU



3D ResNet-34 Architecture

Hara, Kensho, Hirokatsu Kataoka, and Yutaka Satoh. "Learning spatio-temporal features with 3D residual networks for action recognition." *Proceedings of the IEEE International Conference on Computer Vision*. 2017.

Spatio-Temporal Features



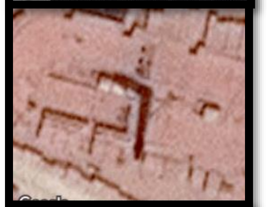
2011 2013 2017

Dataset

Houses

Roads

Kilns



Parking Lots

Sparse Trees

Dense Trees

Orchards

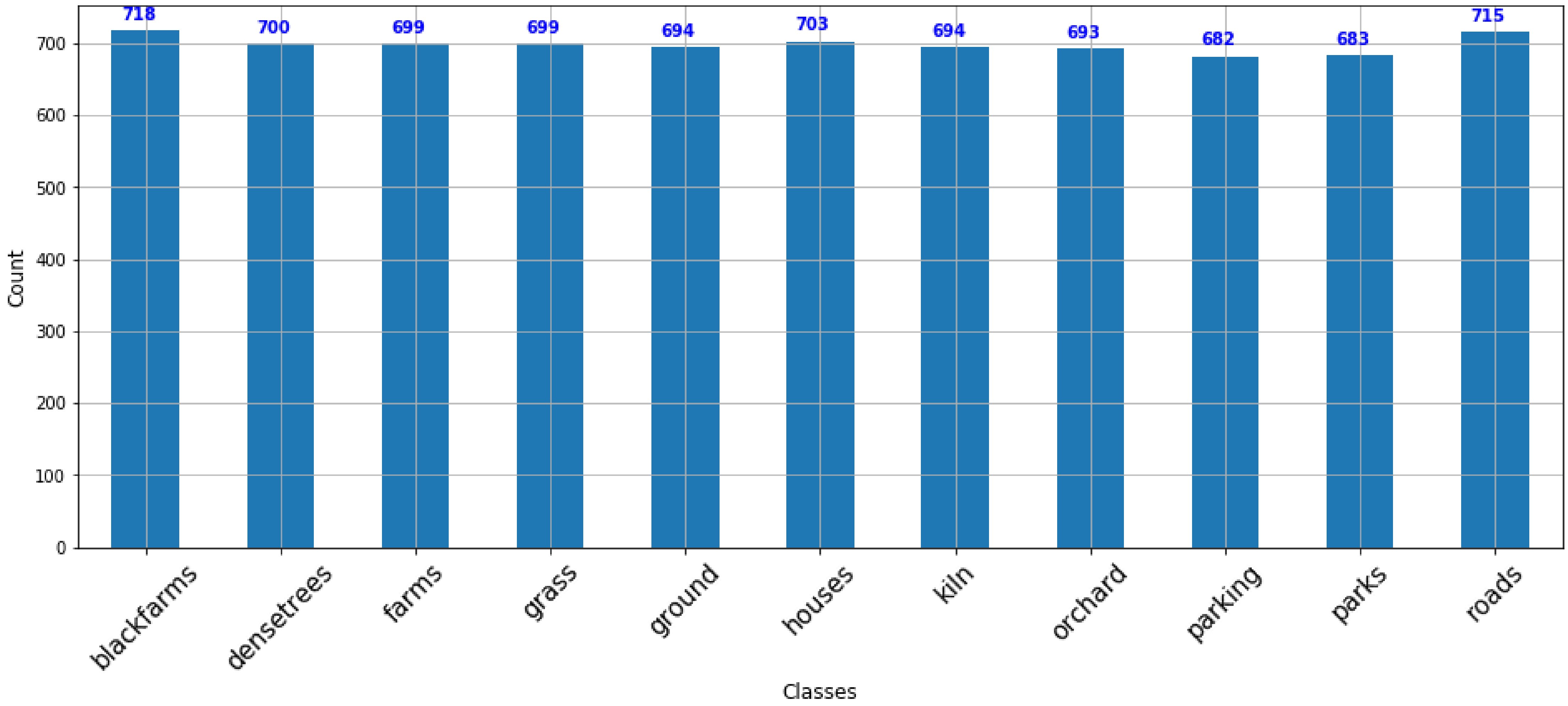
Parks

Grass

Grounds

Farms

Dataset



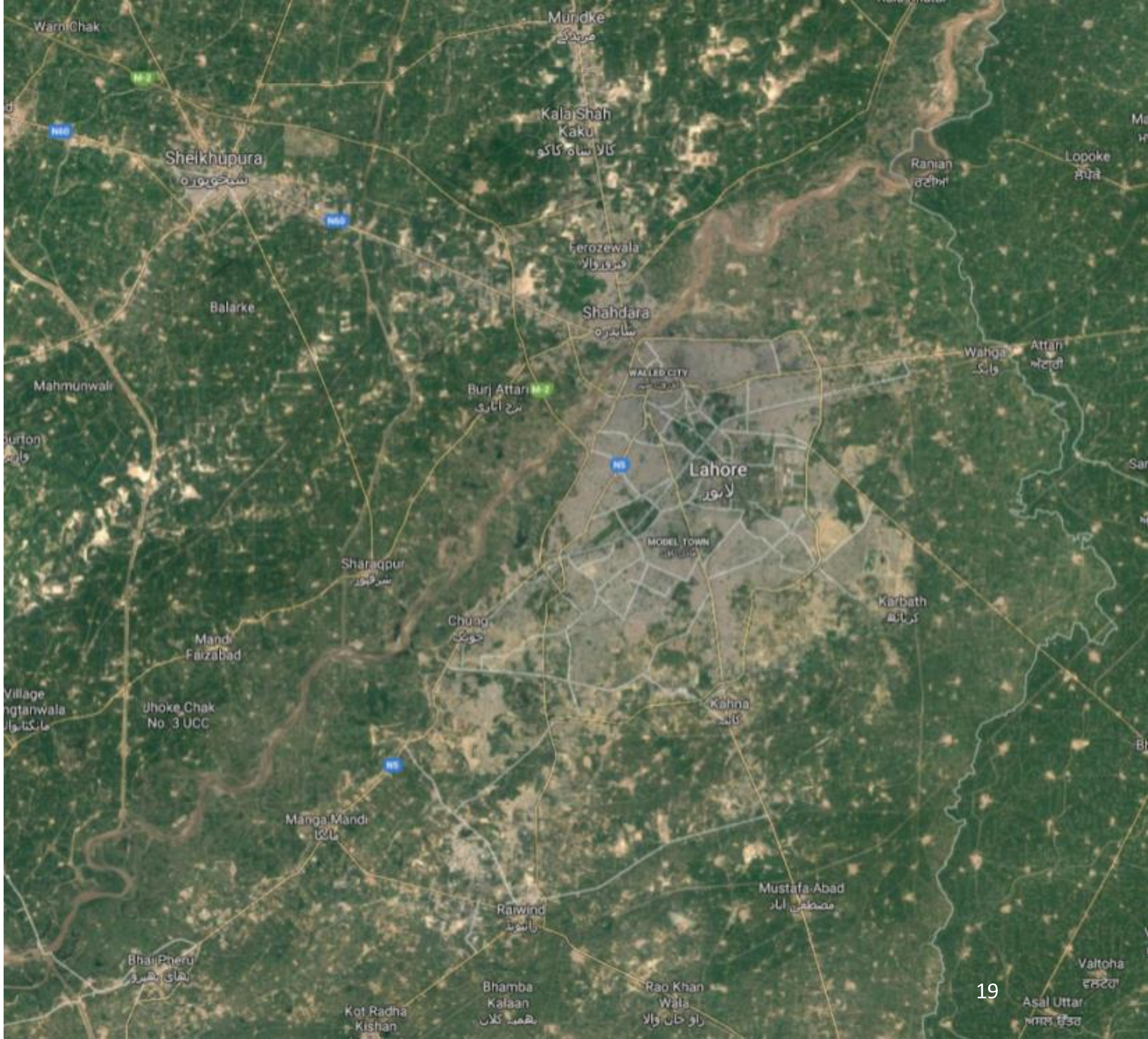
718
700
699
699
694
703
694
693
682
683
715
0
100
200
300
400
500
600
700
Count
blackfarms
densetrees
farms
grass
ground
houses
kiln
orchard
parking
parks
roads
Classes

Dataset

- Labels
  1. Costruction: Anything to House
  2. Destruction: House to Anything
  3. Cultivation: Sparse Trees to Farm or Sparse Trees to Dense Trees
  4. Decultivation: Farm to Sparse Trees

Dataset

- Large dataset size
- Zoom level 20 images
- Renamed with it’s respective latitude and longitude to compare with ground truth data



Results and Evaluation

Cities	Architectures	(Spatio-Temporal Classes) Accuracy					
		Construction	Destruction	Cultivation	Decultivation	No Tras. of Interest	Overall
Aleppo	Inception-ResNet-v2	16.6%	20%	100%	33%	80%	65.95%
	2D-ResNet-50	25%	25%	100%	100%	69%	58.87%
	3D-ResNet-34	33%	30%	51%	33%	54%	42.4%
	Proposed	**71%**	**75%**	**100%**	**100%**	**84%**	**80.14%**

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	3D-ResNet-34	33%	30%	51%	33%	54%	42.4%
	Proposed	**71%**	**75%**	**100%**	**100%**	**84%**	**80.14%**
Khatmandu	Inception-ResNet-v2	24.5%	25%	100%	100%	**77.7**	57.70%
	2D-ResNet-50	31.9%	33%	100%	100%	70.7%	56.45%
	3D-ResNet-34	41.5%	42.3%	100%	100%	65.7%	55%
	Proposed	**48.9%**	**50%**	**100%**	**100%**	65%	**57.72%**

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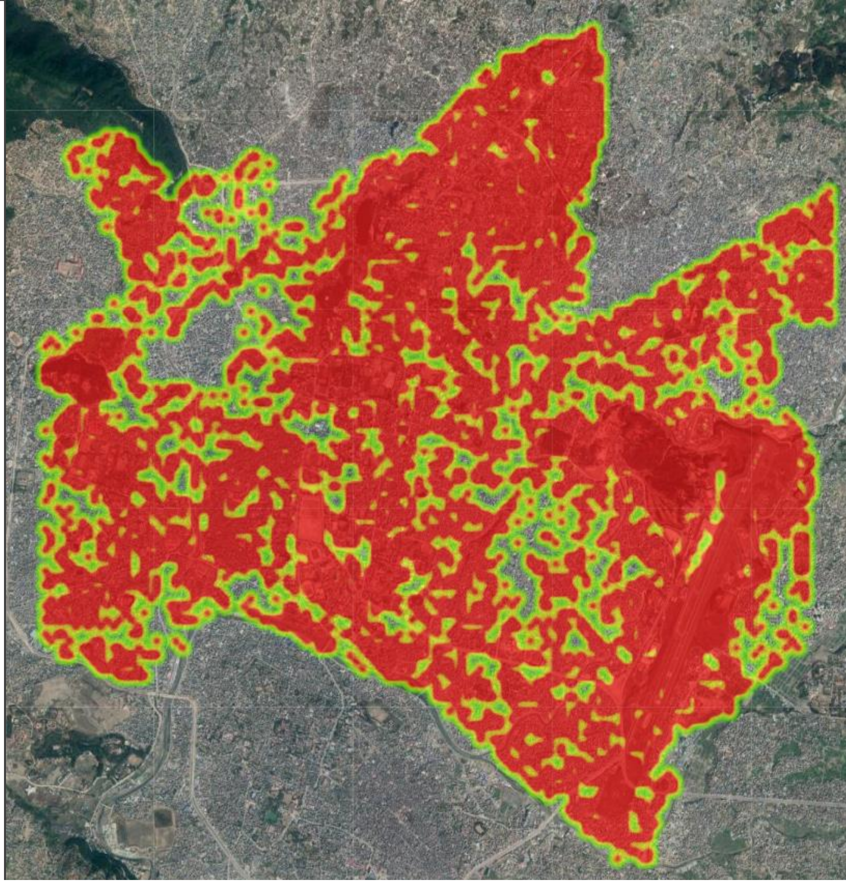
	3D-ResNet-34	41.5%	42.3%	100%	100%	65.7%	55%
	Proposed	**48.9%**	**50%**	**100%**	**100%**	65%	**57.72%**
Lahore	Inception-ResNet-v2	44.8%	45%	**85.7%**	**78.3%**	57.8%	58%
	2D-ResNet-50	53%	55%	71.4%	74%	51.23%	55%
	3D-ResNet-34	50%	49%	71%	37%	40%	60%
	Proposed	**57%**	**58%**	57%	48%	**88.4%**	**75%**





Qualitative Analysis

Conclusion

3D convolutions can learn desired variations in spatio-temporal data

Kathmandu is one of the fastest growing city in world. [Acharya et al. (2015)]

Annotated dataset for four key transitions in remote sensing namely construction, destruction, cultivation and decultivation

Conclusion

3D convolutions can learn desired variations in spatio-temporal data

Kathmandu is one of the fastest growing city in world. [Acharya et al. (2015)]

Annotated dataset for four key transitions in remote sensing namely construction, destruction, cultivation and decultivation

Questions?

For more info. Contact us at cvlab.lums.edu.pk

References

1. Dadras, Mohsen, et al. "Spatio-Temporal Analysis of Urban Growth from Remote Sensing Data in Bandar Abbas City, Iran." *The Egyptian Journal of Remote Sensing and Space Science*18.1 (2015): 35-52
2. Jean, Neal, et al. "Combining Satellite Imagery and Machine Learning to Predict Poverty." *Science* 353.6301 (2016): 790-794
3. Macmanus, et al. "Genocide Achieved, Genocide Continues: Myanmar's Annihilation of the Rohingya." *Genocide Achieved, Genocide Continues: Myanmar's Annihilation of the Rohingya* (2018)
4. Kashif Murtaza, et al. "VillageFinder: Segmentation of Nucleated Villages in Satellite Imagery." The British Machine Vision Conference (2009)
5. Gangaraju, M., et al. "Spatio-Temporal changes of Land Use/Land Cover of Pindrangi Village using High Resolution Satellite Imagery." *Journal of Remote Sensing & GIS* (2017).
6. Hordiiuk, D. M., et al. "Neural Network and Local Laplace Filter Methods Applied to very High Resolution Remote Sensing Imagery in Urban Damage Detection." *2017 IEEE International Young Scientists Forum on Applied Physics and Engineering* (2017)
7. Jean, Neal, et al. "Combining Satellite Imagery and Machine Learning to Predict Poverty." *Science* 353.6301 (2016): 790-794.
8. Acharya, Tri Dev, et al. "Extraction and Modelling of Spatio-Temporal Urban Change in Kathmandu Valley." *Int J IT, Eng Appl Sci Res* 4.3 (2015): 1-11.

Thank you!

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Extra Slide: Dataset

	Brick Kilns	Roads	Parking	Houses	Farms	Dry Farms	Ground	Oil Tanks	Mosque	Parks	Tennis	Ponds	Grass	Dense Trees	Accuracy
Brick kilns	56	3	0	3	0	0	0	2	0	0	0	0	0	1	0.86
Roads	0	56	4	1	0	0	0	2	1	1	0	0	0	0	0.86
Parking	0	4	54	0	0	0	0	0	1	2	1	1	1	1	0.83
Houses	0	8	2	45	0	0	0	0	9	0	0	0	0	1	0.70
Farms	0	0	0	0	65	0	0	0	0	0	0	0	0	0	1.00
Dry Farms	0	0	0	0	6	54	0	0	2	1	0	0	5	0	0.79
Ground	0	0	0	0	0	1	54	1	3	2	0	2	2	0	0.83
Oil Tanks	0	0	0	0	0	0	0	55	3	1	0	0	0	1	0.92
Mosque	0	3	0	19	0	0	0	0	41	0	0	0	0	0	0.63
Parks	0	2	3	0	3	0	0	0	1	43	2	4	2	0	0.72
Tennis	0	0	0	0	0	0	5	0	0	1	43	3	0	0	0.82
Ponds	0	0	0	0	2	19	0	0	0	0	0	50	1	0	0.69
Grass	0	1	0	0	4	0	0	0	0	2	0	13	49	0	0.71
Dense Trees	0	0	0	0	0	0	0	0	0	0	0	17	1	47	0.72