Recognizing Bengali Word Images - A Zero-Shot Learning Perspective

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Motivation

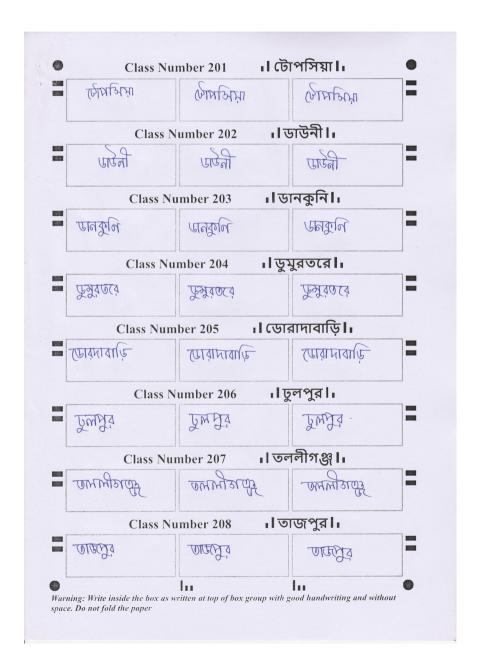
- Deep-learning-based methods are very popular and successful in different classification tasks
- But it demands labeled data for proper training
- Can only deal with "seen" class samples
- LSTMs can recognize "unseen" word classes, but requires fully transcribed text lines and sometimes a language model
- Labeling data demands human intervention, hence costly
- "Zero-shot" learning algorithms with proper feature and class attribute signature can counter this situation

Novelty/Challenges

- Zero-Shot Learning(ZSL) mainly has been explored for object detection
- To the best of our knowledge there is no work on any Indic script word recognition in ZSL perspective
- Signature/Semantic attribute space is very rich in object domain with information on colour and texture but such information is absent in handwritten text

Dataset

- 250 different word classes those are place names in the State of West Bengal in India
- Data collection form contains 8 classes with space to provide 3 samples of handwriting for each class



Dataset

• Elastic morphing based off-line data augmentation

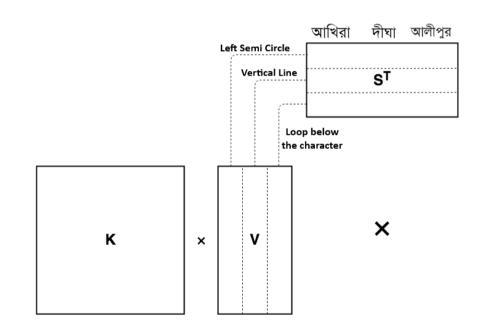
Data	Fold 0	Fold 1	Fold 2	Fold 3	Fold 4
Training	47360	47412	47300	47340	47370
Validation	11790	11800	11774	11780	11790
Testing	14796	14736	14868	14820	14787

Methodology

- Learning is the mapping of basic shape attributes and deep features in matrix "V"
- K is a regular kernel matrix for example "Gaussian", "Polynomial" etc
- Classification calculated per instance 'k' in K,where K could be a Gaussian Kernel or any other standard kernel function
- Classification $_{Argmax}kVS_{i}^{T}$
- S_i is the signature attribute of ith test class

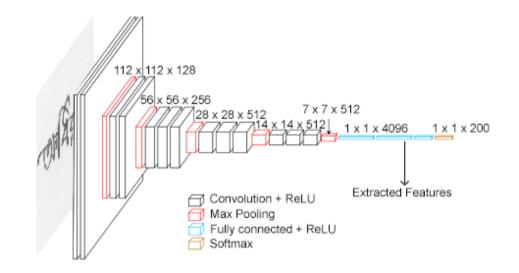
জোড়াবাগান অন্ধিরামপাড়া দরিয়াপুর কালীঘাট

The basic shape attributes marked in red in different Bengali characters



Experimental Framework

- Five-fold cross validation with 50 test classes in each fold
- Different CNN architectures to generate features for word recognition
 - training from scratch
 - no data-flipping inside the architecture
- Features were extracted from output of FC1 layer of VGG16
- For InceptionNet, XceptionNet and ResNet, features were extracted from the average pool layer
- Deep-learned features along with shape attribute signature features are being fed to the Zero-shot learning algorithm



Schematic diagram of our customized VGG16 architecture as used in our experiment.

Results and Discussion

Performance with respect to different signature attributes

Sign. Attribute	Fold 0	Fold 1	Fold 2	Fold 3	Fold 4
S-Alph.	23.88%	32.35%	33.15%	29.66%	19.88%
4S-SpAlph.	49.89%	39.06%	48.98%	49.06%	50.53%

Results and Discussion

Performance with respect to different CNN

Architecture	Fold 0	Fold 1	Fold 2	Fold 3	Fold 4
GoogleNet	35.09%	41.32%	30.28%	28.64%	39.66%
ResNet152	29.26%	28.52%	35.88%	26.07%	27.36%
XceptionNet	44.76%	35.45%	41.43%	38.21%	44.57%

Comparison

Method	Fold 0	Fold 1	Fold 2	Fold 3	Fold 4
AREN*	26.41%	27.24%	31.61%	25.11%	30.31%
Our Method	49.89%	39.06%	48.98%	49.06%	50.53%

^{*} Guo-Sen Xie et al. "Attentive region embedding network for zero-shot learning," in Proc. CVPR, 2019.

Conclusion

• "Unseen" word class images could be recognized using "Zero-shot" learning techniques with shape strokes as attribute signatures

• Efficacy of different CNN architectures were analyzed in the context of ZSL-based word image recognition

Questions!

• Please feel free to contact me during the poster session