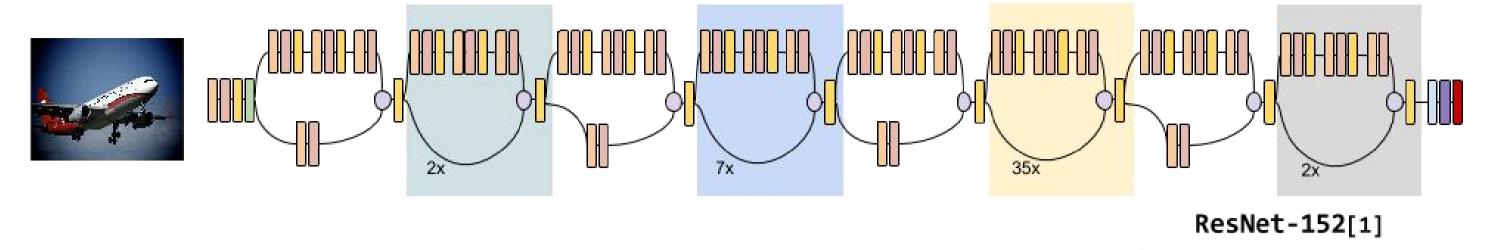


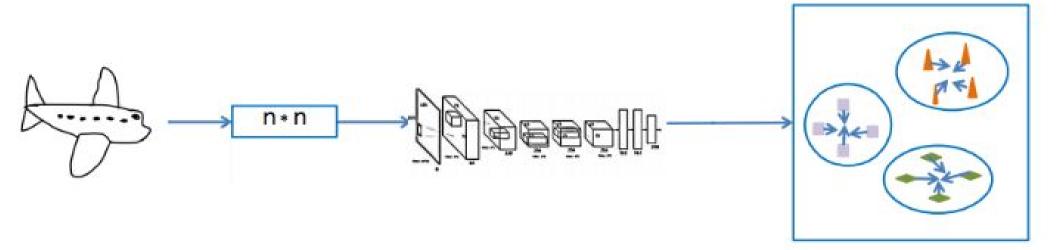
# SwiDeN: Convolutional Neural Networks For Depiction Invariant Object Recognition





#### **CURRENT CLASSIFICATION PARADIGM**

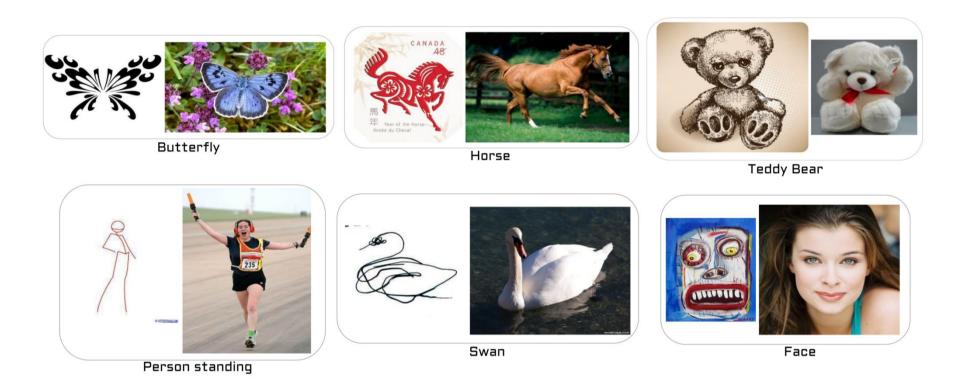




Sketch-a-Net[2]



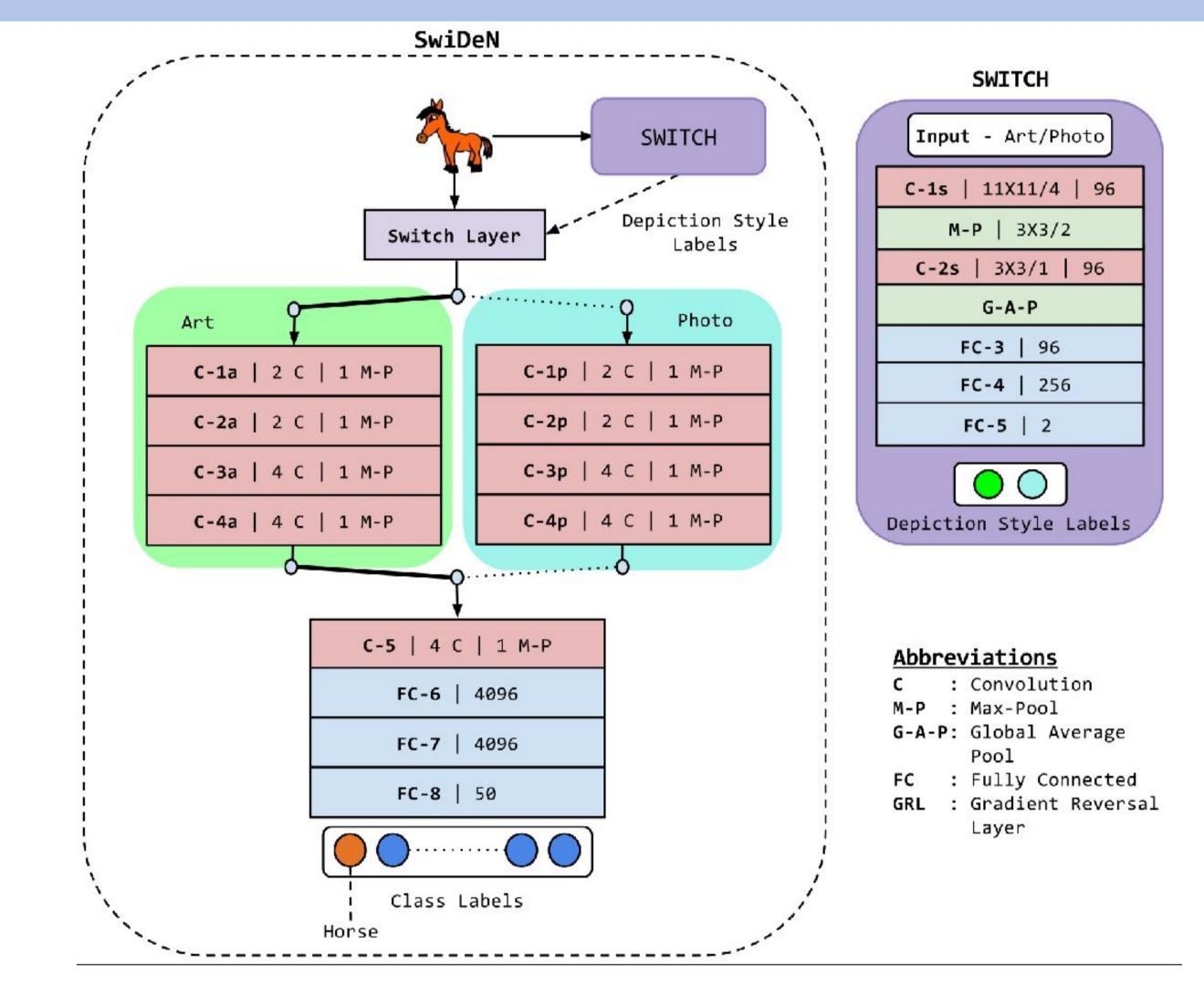
#### **DEPICTION INVARIANT OBJECT RECOGNITION: CHALLENGES...**



#### **Dataset: Photo-Art-50**

- 90-138 images per class.
- Approximately half photo and half art images.
- Contains objects depicted in multiple styles.

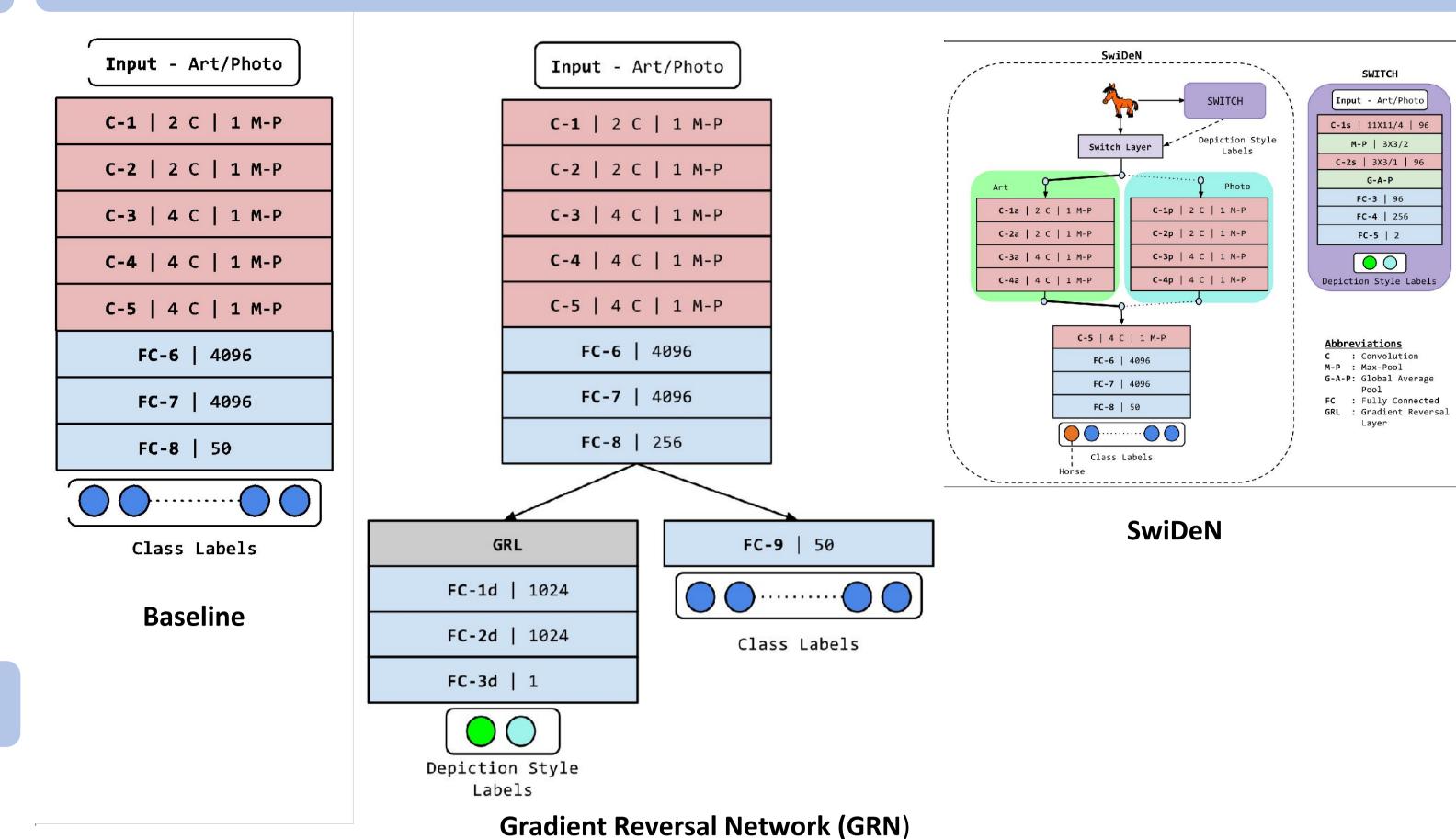
#### **OUR APPROACH: SWITCHING DEEP NETWORK**



#### **SwiDeN: Switching Deep Network**

- Novel `deep' depictive style-based switching mechanism.
- Set of deep sub-networks exist for each depictive style.
- Final set of common layers depiction-invariant learn representation.
- Custom **SWITCH** network serve as a relay mechanism between the initial depiction-specific sub-networks and the shared, deeper depiction-invariant layers.
- SwiDeN and SWITCH are trained using transfer learning with batch stochastic gradient descent.
- Code available at https://github.com/val-iisc/swiden

#### **OTHER APPROACHES**



**RESULTS** 

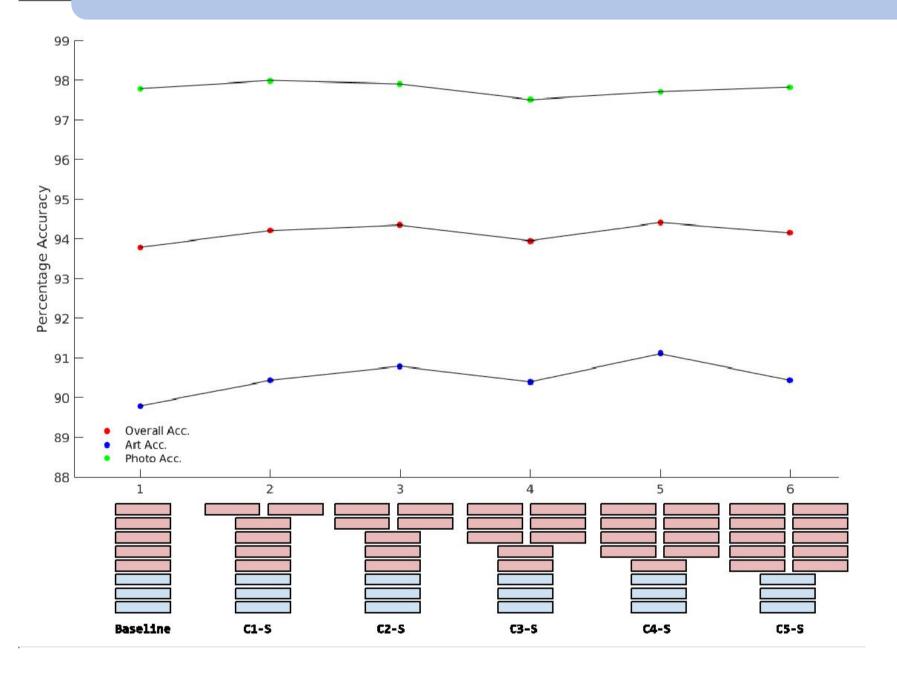
ARCH.	OVERALL ACC.	ART ACC.	Рното Асс.
Baseline	93.80%	89.80%	97.80%
GRN	92.64%	88.52%	96.76%
SwiDeN(Ours)	94.42%	91.12%	97 72%

|SwiDeN(Ours)| 94.42% |91.12%| 97.72% | Table 1: Classification accuracy for different architectures.

Arch.	OVERALL ACC.	ART ACC.	Рното Асс.
Wu et al.[7]	89.67%	89.06%	90.29%
SwiDeN (Ours)	$\boldsymbol{93.02\%}$	88.47%	$\boldsymbol{97.56\%}$

Table 2: Classification accuracy on train-test splits by Cai et al. [3].

#### **ANALYSIS**



Average classification accuracy for different • **SwiDeN** architectures

 As depth of depiction sub-networks increase, we observe that the general classification accuracy and classification accuracy shows an upward trend.



misclassified by **SWITCH**. **SWITCH** achieves an average

- accuracy of 83.7% (80.6% for 'Art' and 86.8% for 'Photo').
- **SWITCH's** inability to achieve accuracy can attributed to the fact that some photo images have a predominantly artistic quality and vice-versa.

### REFERENCES

- [1] He, Kaiming, et al. "Deep residual learning for image recognition." arXiv preprint arXiv:1512.03385 (2015).
- [2] Yu, Qian, et al. "Sketch-a-net that beats humans." arXiv preprint arXiv:1501.07873 (2015).
- [3] Wu et al. Learning graphs to model visual objects across different depictive styles, ECCV 2014.

## T-SNE VISUALIZATIONS

