# Extending Unsupervised Neural Image Compression With Supervised Multitask Learning

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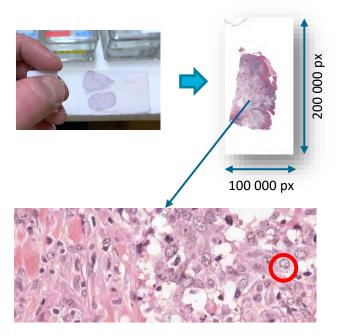
# Introduction to Histopathology Imaging



**Demo Whole-Slide Image** 

Image credits: pixabay.com, 3Dhistech.com

### Digitized Histopathology Sections Are Huuge



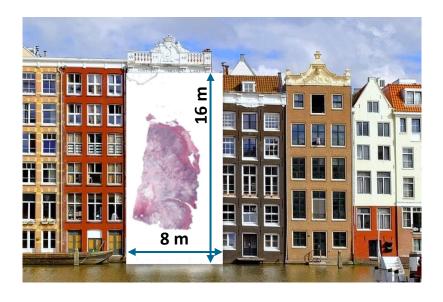
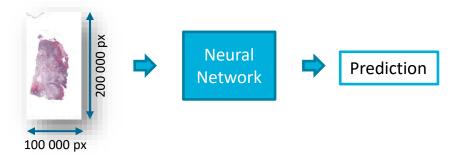


Image credits: pixabay.com, camelyon16.grand-challenge.org

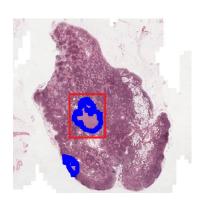
## **Problem Statement**

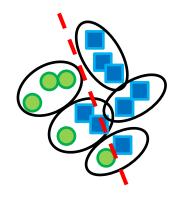
- Task: classify patients based on histopathology imaging
  - Input: gigapixel RGB image
  - Output: patient label (survival, recurrence, response, -omics, biomarkers, etc.)

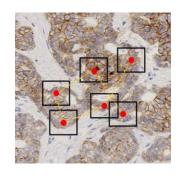


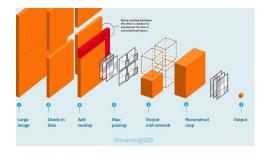
- Constraints:
  - Single-GPU during training and testing
  - No pixel-level task associated with patient label
  - Limited number of patients (<1000 images)</li>

## **Prior Work**









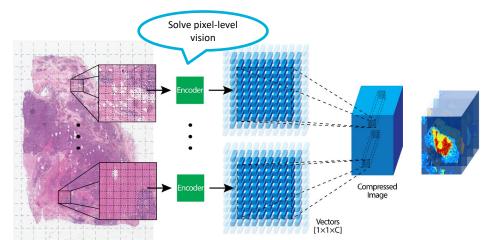
**Pixel annotations**Requires proxy task
Requires annotations

Multiple Instance Learning
Does not exploit relations
among instances

Reinforcement learning
Unstable training
Unexplored areas

Memory Efficient Training
Overfitting due to lack of
training samples

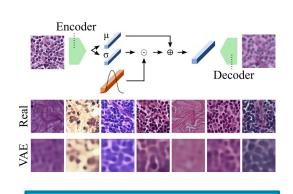
# **Proposed: Neural Image Compression**



- ✓ Single-GPU
- ✓ No pixel-level association with label
- ✓ Limited number of patients
- ✓ Local and global context

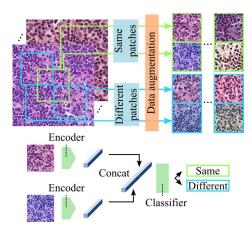


# **Previous Work: Unsupervised Encoder**



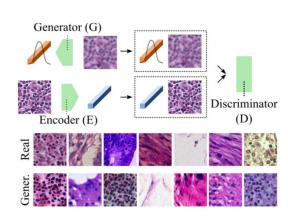
#### Variational autoencoder

$$\begin{aligned} \mathcal{V}_{\text{VAE}}(x, n, \theta_E, \theta_D) &= \\ &= \min_{E, D} \left[ \underbrace{\left(x - D(E(x, n))\right)^2}_{\text{Reconstruction error}} + \underbrace{\gamma(1 + \log \sigma^2 - \mu^2 - \sigma^2)}_{\text{KL divergence}} \right] \end{aligned}$$



#### Contrastive learning

(self-supervised learning)



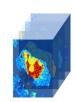
#### **Bidirectional GAN**

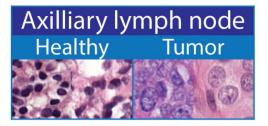
$$\begin{split} & \mathcal{V}_{\mathsf{BiGAN}}(x, z, \theta_G, \theta_E, \theta_D) = \\ & = \min_{G, E} \max_{D} \left[ \log \left[ D \big( x, \underbrace{E(x)} \big) \right] + \log \left[ 1 - D \big( \underbrace{G(z)} , z \big) \right] \right] \end{split}$$

Tellez, David, et al. "Neural Image Compression for Gigapixel Histopathology Image Analysis." TPAMI 2019.

# **Proposal: Supervised Encoder**

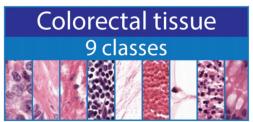






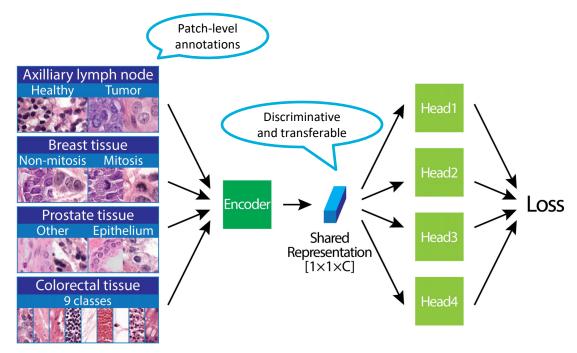




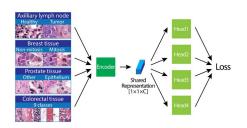


Pixel-level annotations unrelated to patient label

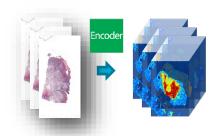
# **Supervised Multi-Task Learning**



### **Neural Image Compression with Multi-Task Encoder**



1. Train Encoder with Multi-Task Learning

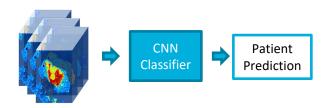


2. Compress All Whole-Slide Images



3. Train Model at Patient Level

# **Experimental Results on TUPAC**





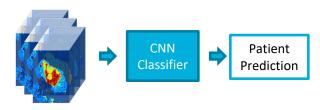
Breast tissue

PAM50 Tumor Profiling Test

- 500 training images
- Label: **speed of tumor proliferation** from molecular profiling (float [-1, +1])
- Additional: 300 test images with labels known by organizers only

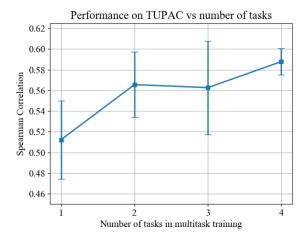
Image credits: tupac.tue-image.nl

## **Experimental Results on TUPAC**



Method	Training set	External test set
NIC unsupervised (Tellez et al., 2019)	0.522	0.558 [0.5191, 0.5962]
Streaming CNNs (Pinckaers et al., 2019)	-	0.570
TUPAC16 winner (Veta et al., 2019)	-	0.617
NIC multitask (proposed)	0.620	$0.632\ [0.5966, 0.6641]$

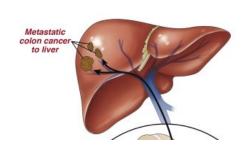
Predicting tumor proliferation speed



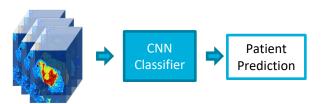
#### Main results:

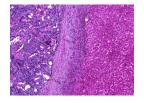
- State-of-the-art result and first place in challenge leaderboard
- Validates the use of supervised multitask learning for gigapixel image-level prediction
- Performance increases with the number of tasks used to train the encoder

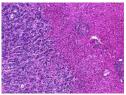
## **Experimental Results on Liver**

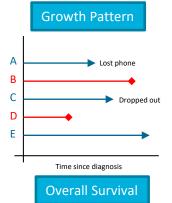


- Liver metastasis of colon cancer
- 1500 training images
- Label 1: type of growth pattern (binary classification)
- Label 2: patient outcome (overall survival)







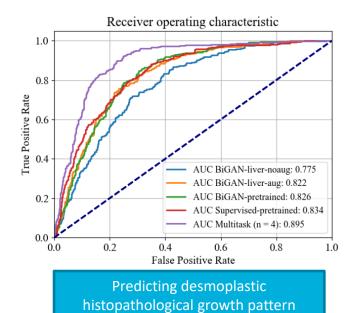


mage credit

Zarour, Luai, et al. "Colorectal cancer liver metastasis: evolving paradigms and future directions." Cellular and molecular gastroenterology and hepatology 2017.

Höppener, Diederik, et al. "Enrichment of the tumour immune microenvironment in patients with desmoplastic colorectal liver metastasis." British Journal of Cancer 2020.

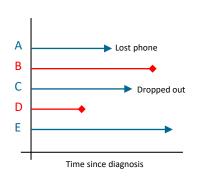
# **Experimental Results on Liver (growth)**



#### Main results:

- Validates the use of supervised multitask learning for gigapixel image-level prediction
- Heavy color augmentation improves performance
- Supervision with 1 task is similar to unsupervised
- Multitask supervision provided the best result

# **Experimental Results on Liver (survival)**

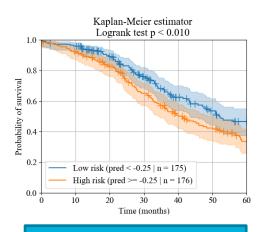


$$\hat{\theta} = \arg\max\log\prod_{i\in D} \frac{\exp f(x_i, \theta)}{\sum_{j\in R_i} \exp f(x_j, \theta)} =$$

$$= \arg\max\sum_{i\in D} \left( f(x_i, \theta) - \log\sum_{j\in R_i} \exp f(x_j, \theta)) \right)$$

D: dead patients; R<sub>i</sub>: set of patients that survived longer than patient i

Sort patients by risk of death



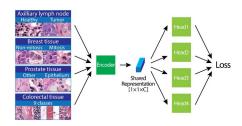
Learning from overall survival

#### Main result:

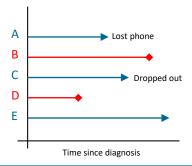
The proposed method can learn directly from patient outcome data (without human annotations)

# **Take-Home Messages**





Multi-task learning improves patient-level classification (even unseen organs)



Predicts patient risk using outcome label data (biomarker discovery)

# Thank You Questions?



**Extending Unsupervised Neural Image Compression With Supervised Multitask Learning** 

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