MULTI-LOSS CONVOLUTIONAL NETWORKS FOR GLAND ANALYSIS IN MICROSCOPY

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CANCER DIAGNOSIS

- Pathologists’ diagnosis involves *simultaneous* feature identification and tumor classification.
Automatic cancer diagnosis often involves independent segmentation and classification steps.
EXAMPLE: GLAND ANALYSIS FOR CANCER DIAGNOSIS

- Glands are reliable bio-markers for different types of adenocarcinoma: colon, breast, prostate, etc.
GLAND ANALYSIS FOR CANCER DIAGNOSIS

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**MOTIVATION**

**GLAND ANALYSIS FOR CANCER DIAGNOSIS**

- **Glands** are reliable bio-markers for different types of adenocarcinoma: colon, breast, prostate, etc.
GLAND ANALYSIS FOR CANCER DIAGNOSIS

› Should the **class** information influence the **segmentation**?
JOINT CLASSIFICATION–SEGMENTATION

- Classification requires segmentation-based features ...

- but generally, segmentation techniques does not involve knowledge of the class ...
JOINT CLASSIFICATION–SEGMENTATION

- We pose the problem of automatic tissue diagnosis as the joint task of segmentation and classification.
- **Goal**: train an end-to-end system to jointly optimize the classification and segmentation predictions.
- Using a deep learning model.
HYBRID CLASSIFICATION-SEGMENTATION NETWORK

Input

CLASSIFICATION SUB-NETWORK

SEGMENTATION SUB-NETWORK

Output

Class-specific spatial priors
CLASSIFICATION SUB-NETWORK

CLASSIFICATION LOSS

\[ \mathcal{L}_C = - \log(Q_y(x)) \]

\[ Q_y(x) = \frac{\exp(z^y(x))}{\sum_{l=1}^{Y} \exp(z^l(x))} \]
CLASS-SPECIFIC SPATIAL PRIORS

$f$ measures the contribution of each layer to the final classification score:

$$f^y_k = \frac{\partial Q_y(x)}{\partial z_k(x)}$$

FULLY CONVOLUTIONAL SEGMENTATION NETWORK
WEIGHTED SEGMENTATION LOSS

\[ \mathcal{L}_S = - \sum_{j=1}^{\Omega} S_j f_j^g \log P_g(x_j) \]

\[ + (1 - S_j) f_j^b \log(P_b(x_j)) \]
**MULTI-LOSS NETWORK**

**CLASSIFICATION LOSS**

\[ \mathcal{L}_C = - \log(Q_y(x)) \]

**SEGMENTATION LOSS**

\[ \mathcal{L}_S = - \sum_{j=1}^{\Omega} S_j f_j^g (\log P_g(x_j)) \]

Proposed Loss = \[ \mathcal{L}_C + \mathcal{L}_S \]

\[ + (1 - S_j) f_j^b \log(P_b(x_j)) \]
**EXPERIMENTS**

- **Dataset:**
  - GLaS gland segmentation challenge, MICCAI 2015 [1].
  - 85 training images: 37 Benign, 48 Malignant.
  - 80 test images: 37 Benign, 43 Malignant.

- **Model training:**
  - Sequential training: 1) Classifier 2) Segmentation 3) Joint fine-tuning.
  - Stochastic Gradient Descent optimization.
  - Implemented in Caffe [2].

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Our hybrid classification-segmentation approach increases the classification accuracy up to 6%.
SEGMENTATION RESULTS

Using class-specific priors increases the segmentation Dice by 6%.

SEGMENTATION RESULTS

For malignant glands, using our hybrid network (using VGG16) increased the segmentation Dice by 13%.
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EXTENDED RESULTS

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Using segmentation priors increased the classification accuracy by 3%.

Using class-specific priors increases the segmentation Jaccard by 2%.
We proposed a novel multi-loss network for simultaneous image segmentation and classification.

We showed that:

1. classification can facilitate the segmentation by introducing class-specific spatial priors.
2. segmentation can benefit classification by providing region-specific features.
THANK YOU.

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