

# AI in Biomedical Imaging

## COMP 3411/9414 Artificial Intelligence

### AI in Computer Vision – Part 3

- Why do we need Biomedical Images?
- Why do we need AI for it?
- Is there any particular challenge in this?
- How do we address these challenges?

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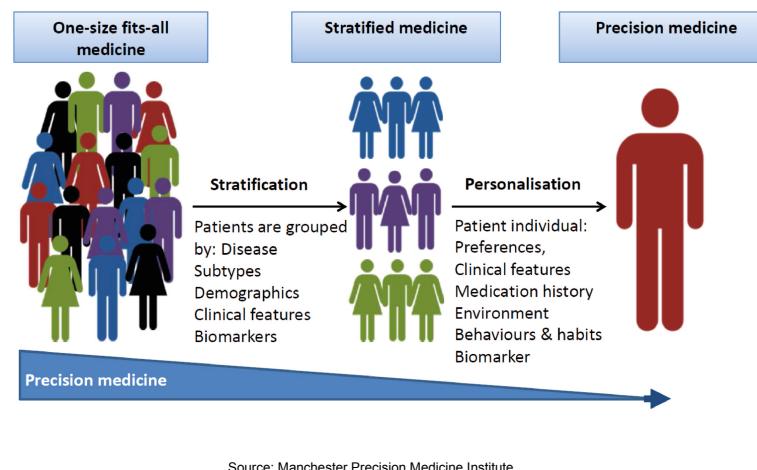
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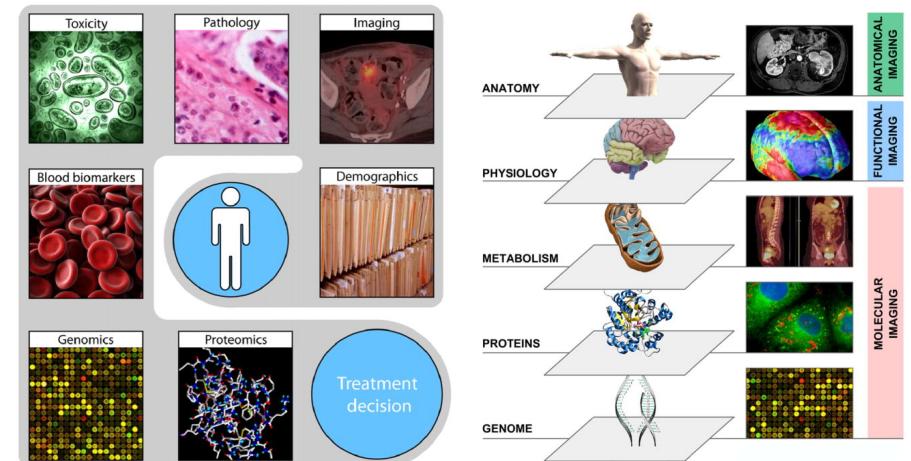
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## Precision Medicine



## Biomedical Imaging in Precision Medicine



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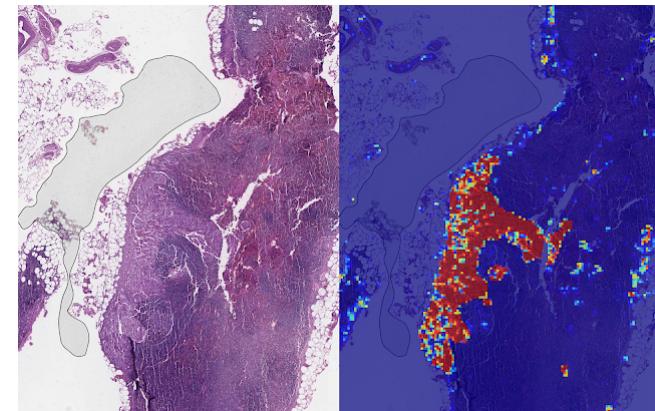
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# AI in Biomedical Imaging

- Biomedical services and research produce lots of imaging data
- With big data, analysis becomes a huge problem
- AI is essential in achieving automated, effective and reproducible analysis of biomedical imaging data
- There are however many unique challenges with biomedical images compared to general non-medical images
- Companies such as GE, Siemens and Google invest heavily in AI-based biomedical imaging applications

# Cancer Detection



Source: <https://ai.googleblog.com/2018/10/applying-deep-learning-to-metastatic.html>

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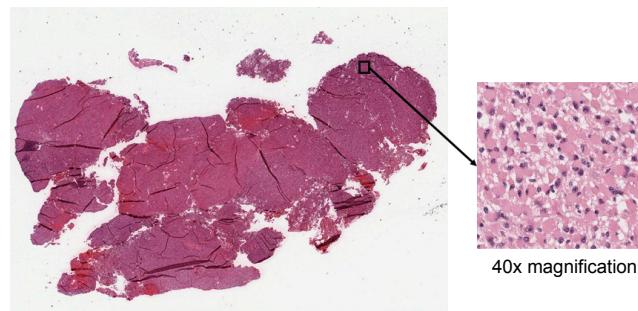
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# Cancer Detection

- Whole-slide image (WSI): very high resolution images
- A shift to fully digital environment for pathology



# Cancer Detection



Source: <https://ai.googleblog.com/2018/10/applying-deep-learning-to-metastatic.html>

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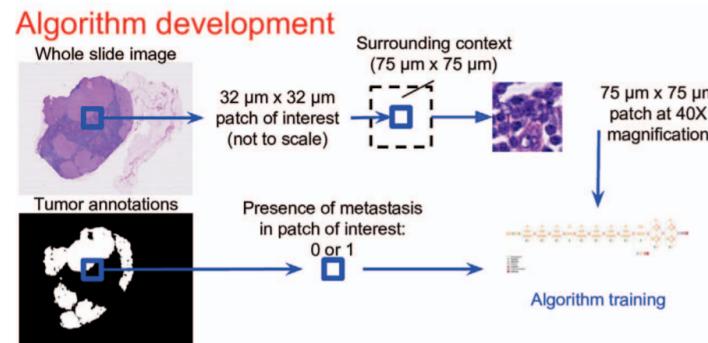
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# Cancer Detection

- Training stage:
  - Patch-wise processing with patch-level labels



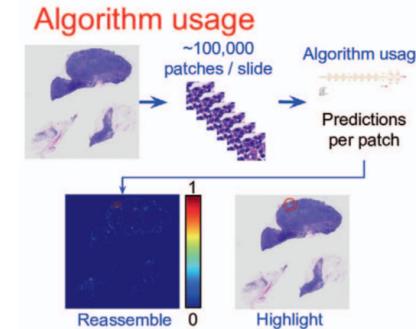
Source: Y. Liu et al. Artificial intelligence-based breast cancer nodal metastasis detection. Arch Pathol Lab Med, 2018.

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- Testing stage:
  - Patch-wise classification



Source: Y. Liu et al. Artificial intelligence-based breast cancer nodal metastasis detection. Arch Pathol Lab Med, 2018.

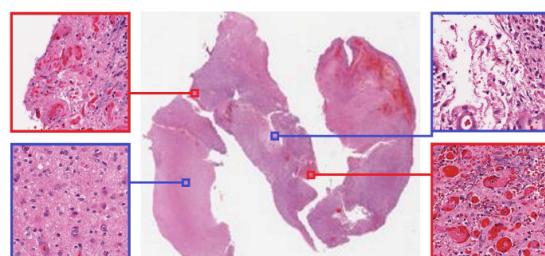
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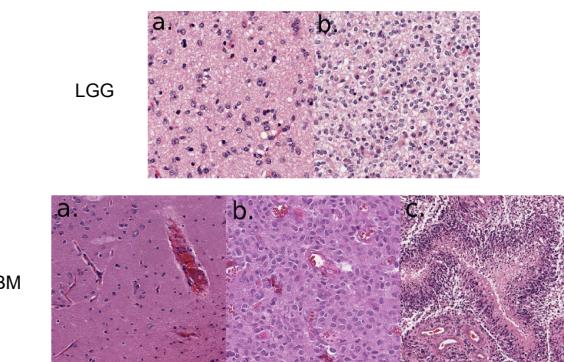
# Real Challenges

- Challenge I:
  - Large image with image-level label only



# Real Challenges

- Challenge II:
  - Histology heterogeneity (subtypes and regional variations)



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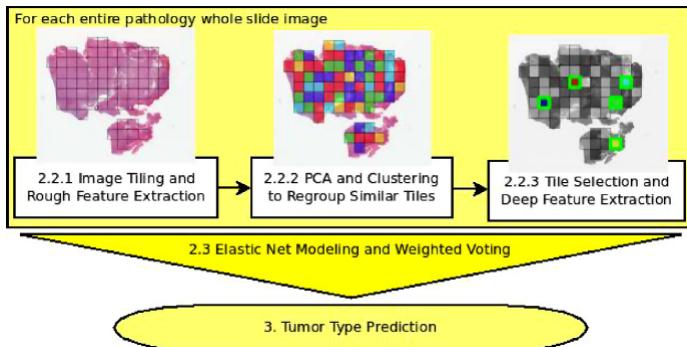
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# Clustering-based

- Coarse and fine feature extraction:



J. Barker et al., "Automated classification of brain tumor type in whole-slide digital pathology images using local representative tiles," *Medical Image Analysis*, 30(1):60-71, 2016.

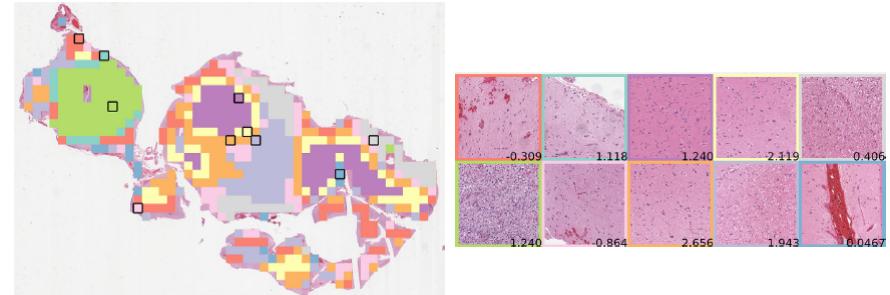
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# Clustering-based

- Coarse and fine feature extraction:
  - Clustering-based representative tile extraction



J. Barker et al., "Automated classification of brain tumor type in whole-slide digital pathology images using local representative tiles," *Medical Image Analysis*, 30(1):60-71, 2016.

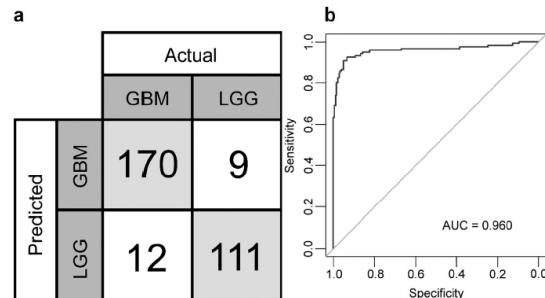
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# Clustering-based

- Coarse and fine feature extraction:



J. Barker et al., "Automated classification of brain tumor type in whole-slide digital pathology images using local representative tiles," *Medical Image Analysis*, 30(1):60-71, 2016.

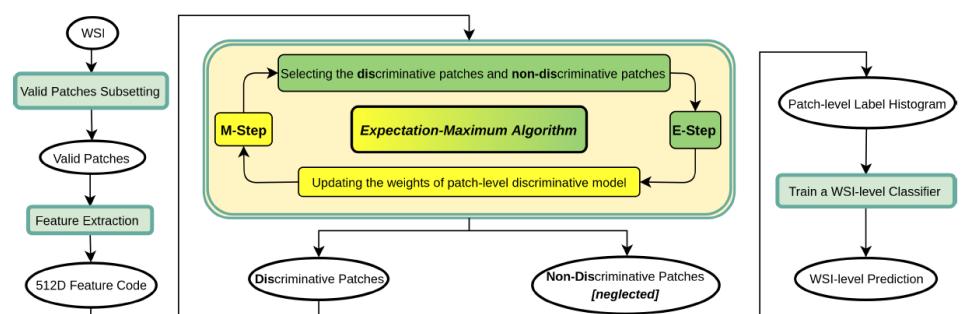
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# Pruning-based

- Discriminative patch-based CNN:
  - EM-based discriminative patch extraction



Source: C. Zhang et al. *Whole slide image classification via iterative patch labelling*. ICIP, 2018.

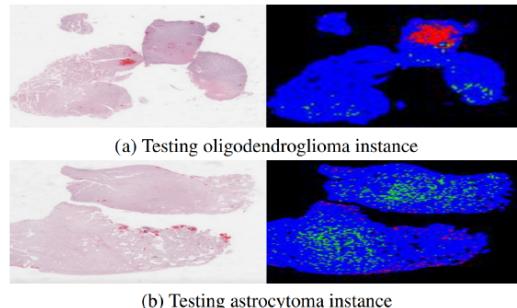
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# Pruning-based

- Discriminative patch-based CNN:
  - EM-based discriminative patch extraction



Source: C. Zhang et al. *Whole slide image classification via iterative patch labelling*. ICIP, 2018.

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- Results on the CBTC challenge dataset:
  - 32 WSI images, with 16 astrocytoma and 16 oligodendrogloma cases

Methods	Acc.
CNN-Feat-SVM	62.50%
Finetune-CNN-Feat-SVM	69.13%
Iter-Finetune-CNN-SVM[Discriminative]	76.62%
<b>Iter-Finetune-CNN-SVM[Both]</b>	<b>84.38%</b>

Source: C. Zhang et al. *Whole slide image classification via iterative patch labelling*. ICIP, 2018.

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## More Studies

- There are many other approaches for WSI analysis.
  - Do a search in *Google Scholar*
  - Keywords: WSI, microscopy, classification, deep learning

WSI microscopy classification deep learning

Any time Since 2018 Since 2019 Custom range Sort by relevance Sort by date Include patents Include citations Create alert

Deep learning for identifying metastatic breast cancer D.Wang, A.Khosla, R.Ganguly. [\[HTML\]](#) arxiv.org

A survey on deep learning in medical image analysis G.Litjens, T.Kooi, B.F.Bergstra, AAA.Sohn, E.Cortes. [\[PDF\]](#) arxiv.org

Deep learning in microscopy image analysis: A Survey E.Xing, Y.Xie, H.Su, F.Liu, Y.Wang. [\[HTML\]](#) networks-and-learning.com

Deep learning methods for histopathological image analysis D.Komura, S.Ishikawa. [\[HTML\]](#) computational-and-structural-biochemistry-journal.com

Deep learning as a tool for increased accuracy and efficiency of histopathological diagnosis P.Mou, Deep learning as a tool for increased accuracy and efficiency of histopathological diagnosis. [\[HTML\]](#) nature.com

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# Pruning-based

- Biomedical imaging is critical in precision medicine.
- There are unique challenges when analysing biomedical images:
  - Insufficient ground truth
  - Highly heterogeneous data
- This is a very active area both in industry and research.

## Summary

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