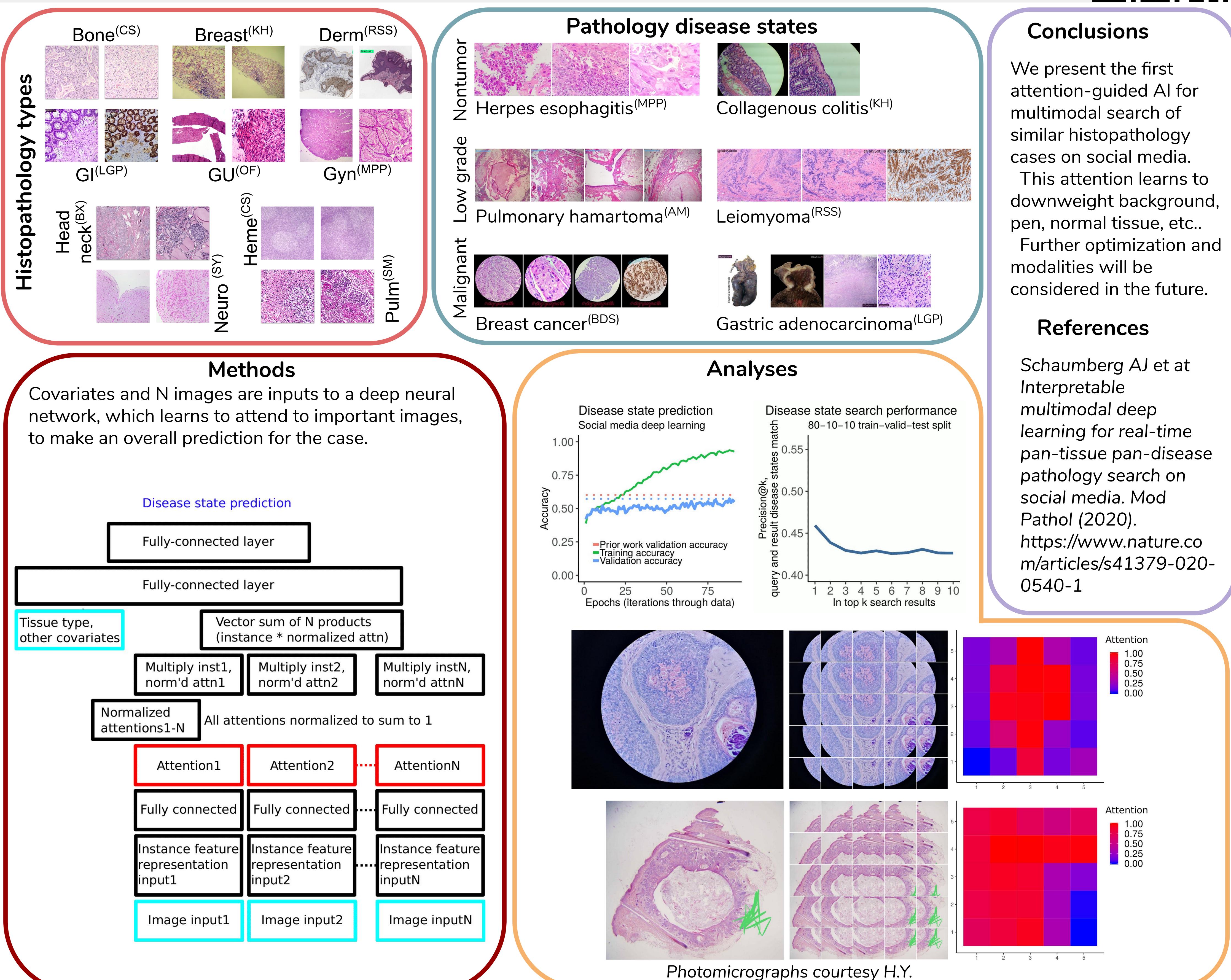# Deep learning of attention-guided multimodal histopathology search on social media

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Problem

A pathologist's process of making a diagnosis is focused, holistic, and robust.

A pathologist fully inspects all slides, carefully attends to informative regions within the slides, jointly considers all informative regions as context, and integrates available complementary clinical information or modalities.

This process has been incredibly challenging to approximate with artificial intelligence [AI].

Solution

Our proposed AI method attempts to model aspects of a pathologist's diagnostic workflow:
1. the AI considers one or more photomicrographs to describe a case,
2. attends to regions of interest within the photomicrograph(s),
3. jointly considers all regions of interest for an overall prediction, and
4. includes possibly-missing covariates such as tissue type.

Platform & data

From social media, we downloaded 19349 images from 8959 Twitter posts from 30 consenting pathologists in 13 countries in 4 continents.

pathobot
1,498 Tweets

pathobot
@pathobot

May find similar #pathology cases. T/RT not medical advice. By @schaumberg_a. Profile pic @dr_MPrieto. Cite nature.com/articles/s4137...

🔗 bitbucket.org/aschaumberg/pa... 📅 Joined February 2019

722 Following   947 Followers

Workflow & appliction

A pathologist posts a case to social media & mentions our bot. Cases like these are data.

A. Celina Stayerman MD @ariella8

Dear #Pulmpath Female on her 70s ,multiple pleural lesions .Your favored diagnosis on morphological basis of this epithelioid /rhabdoid malignant neoplasm and IHC request @pathobot 😊🙏

B. pathobot @pathobot

1 twitter.com/ariella8/statu...   5 twitter.com/smlungpathguy/...
2 twitter.com/ariella8/statu...   6 twitter.com/smlungpathguy/...
3 twitter.com/smlungpathguy/... 7 twitter.com/DrGeeONE/statu...
4 twitter.com/DrGeeONE/statu... 8 twitter.com/smlungpathguy/...

C. pathobot @pathobot

1 ncbi.nlm.nih.gov/pmc/articles/P... 5 ncbi.nlm.nih.gov/pmc/articles/P...
2 ncbi.nlm.nih.gov/pmc/articles/P... 6 ncbi.nlm.nih.gov/pmc/articles/P...
3 ncbi.nlm.nih.gov/pmc/articles/P... 7 ncbi.nlm.nih.gov/pmc/articles/P...
4 ncbi.nlm.nih.gov/pmc/articles/P... 8 ncbi.nlm.nih.gov/pmc/articles/P...

D. pathobot @pathobot

Not medical advice. May be inaccurate.

Disease state prediction findings: Malignant disease (probability 0.925).

Evidence weak, be skeptical.

For research only. Always consider pathologist opinions over computational methods.

Histopathology types

Bone[(CS)]   Breast[(KH)]   Derm[(RSS)]
GI[(LGP)]   GU[(OF)]   Gyn[(MPP)]
Head neck[(BX)]   Heme[(SY)]
Neuro[(SY)]   Pulm[(SM)]

Pathology disease states

Nontumor
Herpes esophagitis[(MPP)]   Collagenous colitis[(KH)]

Low grade
Pulmonary hamartoma[(AM)]   Leiomyoma[(RSS)]

Malignant
Breast cancer[(BDS)]   Gastric adenocarcinoma[(LGP)]

Methods

Covariates and N images are inputs to a deep neural network, which learns to attend to important images, to make an overall prediction for the case.

Disease state prediction

Fully-connected layer

Fully-connected layer

Tissue type, other covariates → Vector sum of N products (instance * normalized attn)

Multiply inst1, norm'd attn1 | Multiply inst2, norm'd attn2 | ... | Multiply instN, norm'd attnN

Normalized attentions1-N   All attentions normalized to sum to 1

Attention1 | Attention2 | ... | AttentionN

Fully connected | Fully connected | ... | Fully connected

Instance feature representation input1 | Instance feature representation input2 | ... | Instance feature representation inputN

Image input1 | Image input2 | ... | Image inputN

Analyses

Disease state prediction
Social media deep learning

Disease state search performance
80–10–10 train–valid–test split

- Prior work validation accuracy
- Training accuracy
- Validation accuracy

Accuracy vs Epochs (iterations through data)

Precision@k, query and result disease states match vs In top k search results

Photomicrographs courtesy H.Y.

Conclusions

We present the first attention-guided AI for multimodal search of similar histopathology cases on social media.

This attention learns to downweight background, pen, normal tissue, etc..

Further optimization and modalities will be considered in the future.

References

Schaumberg AJ et at Interpretable multimodal deep learning for real-time pan-tissue pan-disease pathology search on social media. Mod Pathol (2020). https://www.nature.com/articles/s41379-020-0540-1