Explainable Feature Embedding using Convolutional Neural Networks for Pathological Image Analysis

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Background

Pathology
- ➢ To determine treatment of cancer
- ➢ Requiring considerable time and effort
  - ✓ Evaluating vast number of cells in a tissue on a glass slide with a microscope

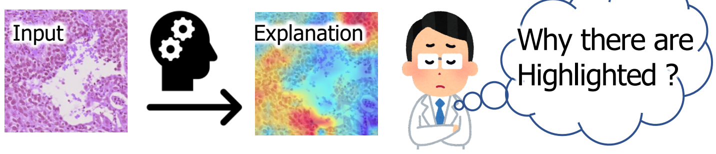
Computer Aided Diagnosis (CAD)
- ➢ Relieve pathologists' burden
- ➢ The use of Convolutional Neural Networks (CNN)
  - ✓ High accuracy for pathological CAD systems
  - ✓ Basis of its decision is hardly interpretable

Accuracy and **Explainability** are required to ensure reliability

Motivation

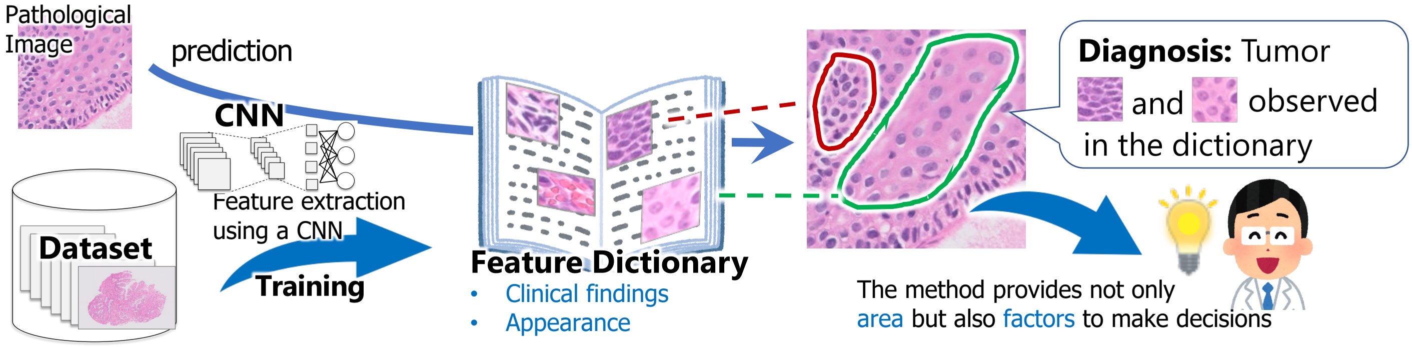
Explainability:
Basis of diagnoses can be interpreted by humans

Related studies for Explainability
Activation based explanations are popular but they cannot tell the reasons for their decisions

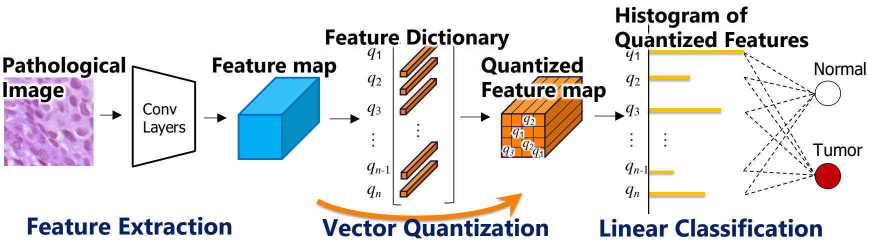


Proposed Method

Main idea: Making decisions by referring a dictionary, which is a collection of interpretable features learned by CNN



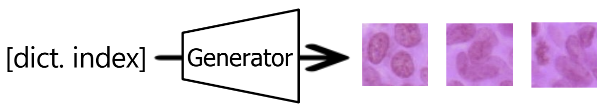
Diagnosis Network
Learning feature extraction and constructing its dictionary in end-to-end fashion
→ Enabling accurate classification



Visualization Network
This network generates images via dictionary's index.
→ Making CNN features interpretable in visual

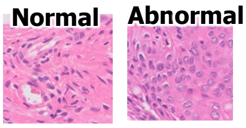
Autoregressive models can generate clear images by directly inferencing image distribution

Conditional Pixel CNN



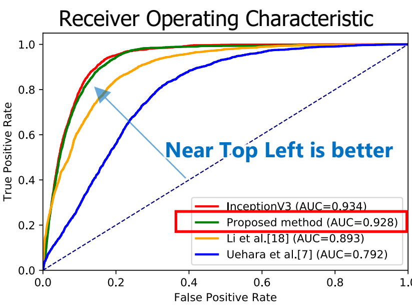
Result and Discussion

Tissue classification
- ➢ Uterine cervix
  - ✓ Normal : Train 84,194 Test 27,601
  - ✓ Abnormal : Train 12,088 Test 2,286
  - ✓ Image size : 256x256 pixel

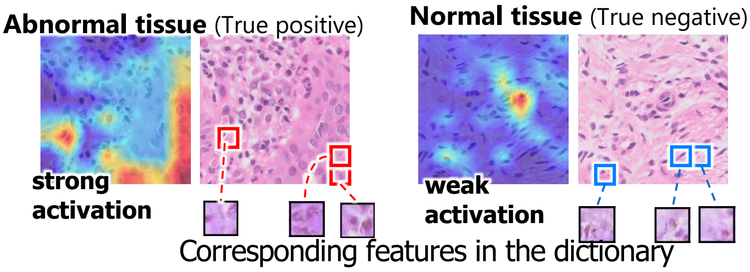


Comparison methods
- ➢ Inception V3 [Liu +, 2017] : **State of the art**
- ➢ ProtoNet [Li +, 2018] : Explainable neural network
- ➢ Dictionary based CNN [Uehara+, 2019] : Explainable neural network

Classification result
- ➢ Our method yielded **0.93 of AUROC**
  - ✓ Comparable to SOTA
  - ✓ Better than other explainable CNNs
- ➢ Learning dictionary in end-to-end fashion was effective



Explanations
Redder area is important for classifying atypical tissue



Conclusion
- Our method brings great advantages compared with the conventional methods in terms of accuracy and explainability
- We plan to confirm the features in the dictionary from a pathology viewpoint