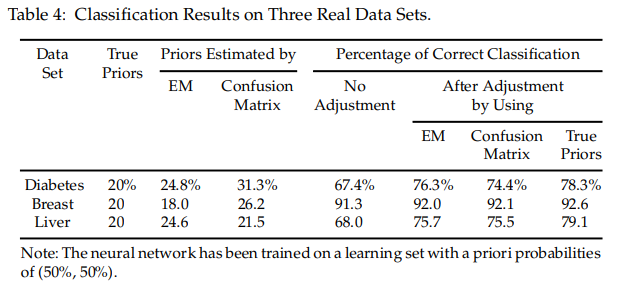
1. 심혈관 질병 다음으로 주요한 사망 원인이다.
   1. IHME, Global Burden of Disease (2019)
2. 추세를 고려할 때, 암은 21세기 중에 심혈관 질병보다 높은 사망률을 가지게 될 것으로 추측된다.
   1. Bray, F., Laversanne, M., Weiderpass, E., & Soerjomataram, I. (2021). The ever‐increasing importance of cancer as a leading cause of premature death worldwide. *Cancer*, *127*(16), 3029-3030.
3. 2025년까지 종양학 서비스에 대한 수요가 42% 이상 증가하는 반면 종양학자의 공급은 28%만 증가할 것으로 추정한다. [내용 수정]
   1. American Society of Clinical Oncology. (2014). The state of cancer care in America, 2014: a report by the American Society of Clinical Oncology. *Journal of Oncology Practice*, *10*(2), 119-142.
4. **[추가]** A 2017 survey conducted by the UK Royal College of Pathologists found adequate staffing in only 3% of National Health Service histopathology departments
   1. Martin, J. (2018). Meeting pathology demand: Histopathology workforce census. *London: Royal College of Pathologists*.
5. **[추가]** As a percentage of total US physicians, pathologists decreased from 2.03% to 1.43%.
   1. Metter, D. M., Colgan, T. J., Leung, S. T., Timmons, C. F., & Park, J. Y. (2019). Trends in the US and Canadian pathologist workforces from 2007 to 2017. *JAMA network open*, *2*(5), e194337-e194337.
6. 진단해야 할 조직 샘플이 24시간 생성되는 특성 상 (병리학자들이) 업무 과중에 놓이기 쉽다
   1. Maung, R. (2016). Pathologists' workload and patient safety. *Diagnostic Histopathology*, *22*(8), 283-287.
7. 전문적인 QA/QI가 병리학자의 주요 의무가 됨에 따라 연간 업무량이 20% 가량 증가했다.
   1. “In the 2014 CAP-ACP (Canadian Association of [Pathologist](https://www.sciencedirect.com/topics/medicine-and-dentistry/pathologist) – Association Canadienne des Pathologistes) workload model, QA/QI work is fully integrated into the system and to accommodate this, the annual work unit per FTE was increased by 20%” 로부터 발췌
   2. Maung, R. (2016). Pathologists' workload and patient safety. *Diagnostic Histopathology*, *22*(8), 283-287.
8. (캐나다에서 unpublish된 데이터에 따르면, 병리학자의) 연간 상담 업무량이 매년 5~10% 가량 증가하고 있다
   1. Maung, R. (2016). Pathologists' workload and patient safety. *Diagnostic Histopathology*, *22*(8), 283-287.
9. 182 participants in the study, 99.7% reported some level of burnout
   1. Kasbi, F., Kaviani, S., Mokhlessin, M., Monshizadeh, L., Noruzi, R., & Kia, N. S. (2018). Job burnout among Iranian speech and language pathologists. *Middle East Journal of Rehabilitation and Health*, *5*(3).
10. The adverse quality and safety impacts increased sharply when worked more than 39 hours/week [RCPA, 2011].
    1. Royal College of Pathologists of Australasia (RCPA). Impact of Workload of Anatomical Pathologists on Quality and Safety (2011)[Internet]. 2011.
11. The average pathologist works 49.2 hours per week
    1. Robboy, S. J., Weintraub, S., Horvath, A. E., Jensen, B. W., Alexander, C. B., Fody, E. P., ... & Black-Schaffer, W. S. (2013). Pathologist workforce in the United States: I. Development of a predictive model to examine factors influencing supply. *Archives of Pathology and Laboratory Medicine*, *137*(12), 1723-1732.
12. Results The rate of inaccurate diagnoses ranged from 3% to 9%
    1. Peck, M., Moffat, D., Latham, B., & Badrick, T. (2018). Review of diagnostic error in anatomical pathology and the role and value of second opinions in error prevention. *Journal of clinical pathology*, *71*(11), 995-1000.
13. There was a significant negative correlation between caseload size and workload satisfaction
    1. Hutchins, Tiffany L., et al. "Retention of school-based SLPs: Relationships among caseload size, workload satisfaction, job satisfaction, and best practice." *Communication Disorders Quarterly* 31.3 (2010): 139-154
14. A lack of job satisfaction contributed significantly to the intention to leave the profession.
    1. Ewen, C., Jenkins, H., Jackson, C., Jutley-Neilson, J., & Galvin, J. (2021). Well-being, job satisfaction, stress and burnout in speech-language pathologists: A review. *International journal of speech-language pathology*, *23*(2), 180-190.
15. DL 서포트 시스템의 목적은 1)진단 정확도 향상, 2) 환자 관리 최적화, 3) 비용 감소이다.
    1. Cui, M., & Zhang, D. Y. (2021). Artificial intelligence and computational pathology. *Laboratory Investigation*, *101*(4), 412-422.
16. WSI 스캐너의 발전이 병리학 프로세스 및 병리학자들의 업무의 디지털화를 가능하게 했다. DL 기술 발전을 통해, 높은 성능의 DL 기반의 서포트 시스템을 많이 활용한다 (Ibrahim et al., 2020).
    1. Ibrahim, A., Gamble, P., Jaroensri, R., Abdelsamea, M. M., Mermel, C. H., Chen, P. H. C., & Rakha, E. A. (2020). Artificial intelligence in digital breast pathology: techniques and applications. *The Breast*, *49*, 267-273.
17. 병리학에 적용된 AI 기술은 다양한 의료 분야에 있어 높은 품질과 정확도의 서비스를 가능하게 해줬다. AI 기술은 병리학자들을 일꾼이 아닌, 감독자로 만들었다
    1. Kayser, K., GĂśrtler, J., Bogovac, M., Bogovac, A., Goldmann, T., Vollmer, E., & Kayser, G. (2009). AI (artificial intelligence) in histopathology--from image analysis to automated diagnosis. *Folia Histochemica et Cytobiologica*, *47*(3), 355-361.

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| **Study** | **Classification** | **Structure** | **Train Dataset** |
| Yan et al.  (2020) | Breast Cancer | Hybrid CNN + LSTM | [Patch] 3771 images from Peking Hospital |
| Man et al.  (2020) | Breast Cancer | DenseNet121-AnoGAN | [Patch] 7909 images from BreaKHis |
| Sun, Xu, et al.  (2020a) | Liver Cancer | DL-based classification  using global labels | [WSI] 462(N 79, AB 383) from TCGA |
| Pati et al.  (2020) | Breast Cancer | HACT-Net | [Patch] 2080 images of 106 WSI from BRACS |
| Xiang et al.  (2022) | Breast / Lung Cancer | DSNet | [WSI] Camelyon16, TCGA-LUSC, BCNB |

* 1. Yan, R., Ren, F., Zihao, W., Wang, L., Zhang, T., Liu, Y., Rao, X., Zheng, C., & Zhang, F. (2020). Breast cancer histopathological image classification using a hybrid deep neural network. *Methods*, **173**, 52–60.
  2. Man, R., Yang, P., & Xu, B. (2020). Classification of breast cancer histopathological images using discriminative patches screened by generative adversarial networks. *IEEE access*, *8*, 155362-155377.
  3. Sun, C., Xu, A., Liu, D., Xiong, Z., Zhao, F., & Ding, W. (2020a). Deep learning-based classification of liver cancer histopathology images using only global labels. *IEEE Journal of Biomedical and Health Informatics*, **24**(6), 1643– 1651.
  4. Pati, P., Jaume, G., Fernandes, L. A., Foncubierta-Rodríguez, A., Feroce, F., Anniciello, A. M., Scognamiglio, G., Brancati, N., Riccio, D., Di Bonito, M., De Pietro, G., Botti, G., Goksel, O., Thiran, J.-P., Frucci, M., & Gabrani, M. (2020). Hact-net: A hierarchical cell-to-tissue graph neural network for histopathological image classification. In C. H. Sudre, H. Fehri, T. Arbel, C. F. Baumgartner, A. Dalca, R. Tanno, K. Leemput, W. M. Wells, A. Sotiras, B. Papiez, E. Ferrante, & S. Parisot (Eds.), *Uncertainty for safe utilization of machine learning in medical imaging, and graphs in biomedical image analysis* (pp. 208– 219). Springer International Publishing.
  5. Xiang, T., Song, Y., Zhang, C., Liu, D., Chen, M., Zhang, F., Huang, H., O'Donnell, L., & Cai, W. (2022). Dsnet: A dual-stream framework for weakly-supervised gigapixel pathology image analysis. *IEEE Transactions on Medical Imaging*, 1–11.

1. (병리학 특성 상)대다수의 정상 표본에 비해 매우 적은 양의 비정상 표본이 나온다.
   1. Zhang, H., Guo, W., Zhang, S., Lu, H., & Zhao, X. (2022). Unsupervised deep anomaly detection for medical images using an improved adversarial autoencoder. *Journal of Digital Imaging*, *35*(2), 153-161.
2. 대부분의 예측 모델은 Imbalance 데이터의 특성을 잘 반영하지 못하여 성능이 악화된다
   1. He, H., & Garcia, E. A. (2009). Learning from imbalanced data. *IEEE Transactions on knowledge and data engineering*, *21*(9), 1263-1284.
3. (Imbalance 데이터셋에 대한 예측 모델은)높은 정확도를 가지나, False negative / False positive의 경우가 많다.
   1. Loyola-González, O., Martínez-Trinidad, J. F., Carrasco-Ochoa, J. A., & García-Borroto, M. (2016). Study of the impact of resampling methods for contrast pattern based classifiers in imbalanced databases. *Neurocomputing*, *175*, 935-947.
4. Imbalance 문제를 해소하는 방법(ex- resampling)은 성능 악화 방지에 한계가 있다.[Maciej, 2008]
   1. Mazurowski, M. A., Habas, P. A., Zurada, J. M., Lo, J. Y., Baker, J. A., & Tourassi, G. D. (2008). Training neural network classifiers for medical decision making: The effects of imbalanced datasets on classification performance. *Neural networks*, *21*(2-3), 427-436.
5. Datashift 정의 참고 [Jose, 2012]
   1. Moreno-Torres, J. G., Raeder, T., Alaiz-Rodríguez, R., Chawla, N. V., & Herrera, F. (2012). A unifying view on dataset shift in classification. *Pattern recognition*, *45*(1), 521-530.
6. ~~[제거] Prior probability shift 을 고려하지 않았을 때 DL 모델의 성능이 악화된다. [Amos, 2013~~
7. **[추가]**Test error generally increases in proportion to the distribution difference between training and test datasets
   1. Ben-David, S., Blitzer, J., Crammer, K., & Pereira, F. (2006). Analysis of representations for domain adaptation. *Advances in neural information processing systems*, *19*.
   2. Torralba, A., & Efros, A. A. (2011, June). Unbiased look at dataset bias. In *CVPR 2011* (pp. 1521-1528). IEEE.
8. [그래프 출처]



* 1. Saerens, M., Latinne, P., & Decaestecker, C. (2002). Adjusting the outputs of a classifier to new a priori probabilities: a simple procedure. *Neural computation*, *14*(1), 21-41.

1. 의료계에 적용된 이상치 탐색 연구들 특징 [Maximilian, 2022].
   1. Tschuchnig, M. E., & Gadermayr, M. (2022). Anomaly Detection in Medical Imaging-A Mini Review. *Data Science–Analytics and Applications*, 33-38.

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| **주요 특징** | **주요 모델명** | **학습 데이터** | **Key Idea** |
| Deviation based | AAE based  (Kim, 2022) | Normal + abnormal | 학습 데이터를 통해 Encoder/Decoder 를 Adversarial 하게 학습.  이후 학습된 Decoder을 활용하여 Abnormal 데이터 구분 |
| Gan based  (Kim, 2020) | Normal + abnormal | 학습 데이터를 통해 Generator/Discriminator 를 Adversarial 하게 학습.  이후 학습된 Discriminator을 활용하여 Abnormal 데이터 구분 |
| Score based | DevNet  (Pang, 2019) | Normal Only | 정규 분포를 통해 데이터가 얼마나 Normal로부터 벗어났는지 수치화 |
| Feature extraction  + ML Method | DeepSAD  (Ruff, 2019) | Normal Only | DL 모델로 데이터의 특징을 추출한 후,  SVM의 손실함수를 활용하여 Abnormal 예측 모델 학습 |
| OCNN  (Oza, 2018) | Normal Only | AE 모델로 데이터의 특징을 추출 후,  OC-SVM의 손실함수를 활용하여 Abnormal 예측 모델 학습 |

* Kim, H. S., Muallifah, N., Cho, Y., Lee, B., & Yi, M. Y. (2022, October). Deep learning-based defect detection on livestock operations. In *Proceedings of the Conference on Research in Adaptive and Convergent Systems* (pp. 21-27).
* Kim, J., Jeong, K., Choi, H., & Seo, K. (2020, August). GAN-based anomaly detection in imbalance problems. In *European Conference on Computer Vision* (pp. 128-145). Springer, Cham.
* Pang, G., Shen, C., Jin, H., & Hengel, A. V. D. (2019). Deep weakly-supervised anomaly detection. *arXiv preprint arXiv:1910.13601*.
* Ruff, L., Vandermeulen, R. A., Görnitz, N., Binder, A., Müller, E., Müller, K. R., & Kloft, M. (2019). Deep semi-supervised anomaly detection. *arXiv preprint arXiv:1906.02694*.
* Oza, P., & Patel, V. M. (2018). One-class convolutional neural network. *IEEE Signal Processing Letters*, *26*(2), 277-281.