An Extensive Survey on Various Tumor Detection in Histopathological Images Using Deep Learning Techniques

Monika Subramanian[1(✉)], Nagarajan Ganesan[1], and SathishKumar Balasubramaniyan[2]

[1] Department of Electronics and Communication, Puducherry Technological University, Puducherry, India
monika.s@pec.edu

[2] Department of Electronics and Communication, AVC College of Engineering, Mayiladuthurai, Tamil Nadu, India

Abstract. Nowadays Biomedical Image Processing is the most developing field and its demand also more in various growth of several applications. Research into these medical technologies has many features and applications. It includes a variety of imaging modalities that can analyze, enhance, and display images from X-ray, ultrasound, MRI, nuclear medicine, and optical imaging techniques. Those features extracted from suspect regions of the images will help them find the place where the tumor is present in real-time and is useful for speeding up the treatment process. Over the last few years, a tomographic image shows poor qualities which are not specific to metastasis. It is expensive compared with Histopathological images which provide high-resolution images at a low cost. The main motivation to select a Histopathological image over a tomographic image is that a tomographic image is a preoperative diagnosis, whereas Histopathological images provide both a preoperative diagnosis and provide a prognostic assessment of post-disease treatment (surgery) for effective decision-making regarding further treatment. Moreover, in artificial intelligence, deep learning algorithms have become the successors of pathology image analysis for tumor area segmentation, identification, metastasis detection and patient prediction. So, depending upon the development of deep learning advancements in Histopathological Images, a comparison of deep learning algorithms is surveyed and the deep learning algorithms deal with high-level features in detecting tumors using Histopathological Images.

Keywords: Deep Learning · Filtering Techniques · Histopathological images · Tumor detection · Whole slide images

1 Introduction

The medical imaging goal is to extract useful information and accurate findings from those images with no errors. Over the previous decade, there is a rapid growth in computational power and also the image was enhanced and analyzed. It uses algorithms

B. Raj et al. (Eds.): ICETE 2023, AER 223, pp. 105–118, 2023.
https://doi.org/10.2991/978-94-6463-252-1_13

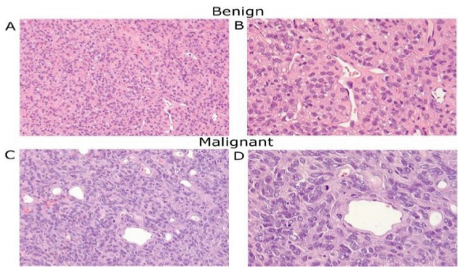

Fig. 1. Solitary Fibrous Tumor (40)

to improve computational approaches to pathological data. Currently, full-slide digital scanners and digitized histopathology slides can be stored in digital image form [1]. CAD algorithms are the rising ones designed for disease detection, diagnosis and prognosis to improve pathologist awareness about diseases [2]. Histopathology is the study of diseased cells and tissues using a microscope. Histopathology slides provide a more complete picture of the disease and also its reaction on tissue [3]. A tumor will develop when the cells start to reproduce too quickly in our body. An abnormal mass of tissue results when cells divide more than they should or do not die when they should. There are different types of tumors starting from a minute nodule to a huge, they can appear more or less in any place on the body. Examples include Carcinoma, Sarcoma, Germ cell tumors, Blastoma and Meningiomas. So not sure about the growth of cells, and will become good or bad. It is always better to check any growth that become starts to benign and that benign become premalignant and that premalignant turns into a malignant tumor. A benign and malignant image of a solitary fibrous tumor is cited in Fig. 1.

The Patients affected by the Most Common Types of Cancer in 2022 were,

- Breast (2.30 million cases)
- Lung (2.28 million cases)
- Colon and rectum (1.99 million cases)
- Prostate (1.49 million cases)
- Skin (non-melanoma) (1.26 million cases)
- Stomach (1.28 million cases)

The Most Common death caused due to Cancer in 2022 was,

- Lung (1.91 million deaths)
- Colon and rectum (9, 16, 052 deaths)
- Liver (8, 30, 103 deaths)
- Stomach (7, 69, 102 deaths)
- Breast (6,85,026 deaths)

1.1 Diagnosis

Sometimes a person could feel some abnormalities in their body, depending upon their condition they will go to a checkup and the doctor will tell treatments or imaging tests,

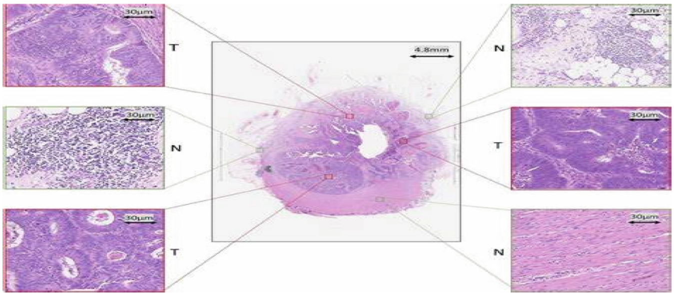

Fig. 2. Nodules and Tumor Region Split-Up (41)

such as tomography and pathological tests. From that test, the technician selects tumor stages. An observation is taken to know the tumor stage or lump. The doctor takes the tissue sample from the patient and those samples are sent to a laboratory and it will undergo a microscope process. Depending upon the results the doctor will decide whether a person requires surgery if a person has a malignant tumor [4]. The development of a tumor for a person will depend upon its stage. Most of the time benign tumors did not bring health risks. But it's better to remove benign stages earlier. If the benign stage develops into premalignant or malignant it may be more challenging to treat severe stages in the future. So it is possible to give treatment in the early stage [5].

1.2 Histopathological Image

Digital recording of pathology gives massive graphic information within easy reach for computerized diagnosis [6]. It has tissue regions in high–resolution information [7]. This helps in imaging data such as stages and grades with a useful quantity of feature imaging [8]. Nowadays Whole Slide Imaging (WSI) shows better imaging. How the WSI can be divided into different forms is shown in Fig. 2.

Countless identification and categorization algorithms of the previous tissues in pathologic images are considered for the research development [9]. The best algorithms for pathologic function and biomedical image scanning are used for preserving information with artificial intelligence techniques [10]. A brief of various methods will give pathology report images, their details of the algorithms which are designed for those images has an irregular region of types various highlighted [11].

2 Methodologies

In artificial intelligence, after machine learning Deep learning is a part that trains computer systems to carry out human intelligence. It is a key era in the back of driverless cars, allowing them to understand a forestall signal or to differentiate a pedestrian from a lamp post. It is one of the rising fields in scientific imaging [12]. It also achieves reputation accuracy at better stages than ever before. So, it's a higher desire to apply withinside the biomedical imaging subject for the detection of sicknesses in addition to enhancing the overall performance of scientific subjects [13].

In healthcare, cancer researchers are the usage of deep studying to robotically come across most cancer cells [14]. Deep studying fashions are educated with the aid of using the usage of massive units of labeled statistics and neural community architectures that analyze functions without delay from the statistics without the want for guide characteristic extraction [15]. In this Fig. 3 depicts the version of deep learning.

Convolutional Neural Networks CNN is the one that plays a major role in deep learning models [16]. By using CNN no need for a guide for the extraction of features [17]. The computerized feature extraction will change the learning models more perfect for tasks of object detection [18]. A simple neural network is given in Fig. 4.

Machine learning has different types of techniques and frameworks used for extracting the issues that will be addressed. Comparing the artificial intelligence types of machine learning and deep learning, a high-performance GPU and a more of a number of labeled data are present. In case is a lack of resources then the use of Machine Learning Techniques is applicable. So there is a need for reliable results achieved in less time. Some of the works for Tumor detection using Deep Learning Techniques are discussed as shown in Table 1.

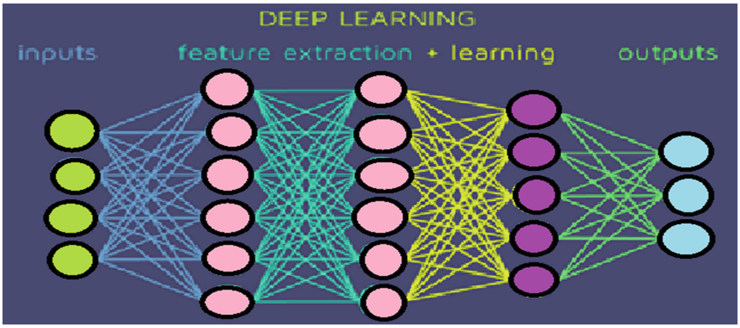

Fig. 3. Deep Learning Model

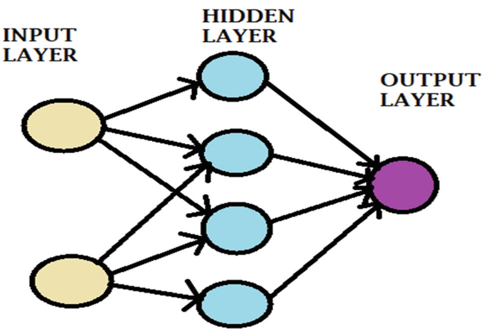

Fig. 4. Neural Network

3 Conclusion

Detailed surveys of various tumor detection techniques using histopathological images that are used in Medical Image Processing are described. From the survey, it seems that tomographic images show poor quality and are expensive compared with histopathological images, whereas histopathological image gives high-resolution image at a low cost. The limitations of this study are Deep learning gives the best only with huge numbers of data. Among the various tumor detection techniques, Deep learning methods are found to a strong, especially for tumor finding. The future scope will be able to extend the convenience and adaptability of WSI image-based tumor identification.

Table 1. Record of Various Tumor Detection Using Deep Learning Techniques

Ref	Year	Inference	Design Methodology
19	**2020**	Bit-by-bit it is performed on the bag level to the identical with not originate patches. The multiple instance CNN framework makes the critical regions on a WSI image for learning and with the help of the MI Pool layer WSI image representation. This assigned framework becomes useful and adjustable to Whole slide imaging breast cancer detection tasks. Finally, the overall analysis was evaluated using the Break His, IUP, HL and UCSB breast cancer datasets and the performance was increased to 93.06%, 96.63%, and 95.83%.	A Multiple Instance Learning (MIL) based CNN structure is presented and the MIL has to train in advance the VGG 19 network.
20	**2021**	In this study, a brand-new approach for antibody-supervised schooling of a CNN set of rules is used. The generated set of rules changed into distinctly correct and indicates that the approach of producing schooling units is convenient. The skilled model on Hematoxylin and Eosin-stained tissue regions and that observation created a new protocol in which the pan-leukocyte anti-CD45 antibody marked the information for the Hematoxylin and Eosin-stained specimens. At last, the destain restain protocol and the anti-CD45 Diaminobenzidine are converted to DAB stain and those samples are preferred to be covered on HE-stained specimens.	A set of rules for dividing white blood cells in Papillary Thyroid Carcinoma is designed using ConvNet.

(*continued*)

Table 1. (*continued*)

Ref	Year	Inference	Design Methodology
21	**2021**	This channel of approach indicates a robust and goal attaining of CD8 recognizing primarily based totally on recurring records of pathologic images and have to make contributions over the medical transformation of computing pathology. In this approach additionally, a cancer cells borderline was also founded which was primarily based totally on a sample of tissues kind class of HE stained records and investigated the CD8- superb cells in an IHC photo to provide CD8-superb molecular mass values. An automatic channel approach for the numerical and values of CD8-superb TILs, involving a learning-based tissue sample kind detector on entire slide HE records, a DL found in the middle of nuclei on IHC-sample of stained slide records, and those records are applied on turned into built lucky.	A deep neural network cancer cell kind type set of rules is structured for WSI images of arrangement of phenomenon can recognize and ability to kill cancer cells CD8-superb lymphocytes are produced and at the (HE) sampled tissue phase to pick out the significant cancer cells and metastasis of the tumor.
22	**2011**	A little work to produce bigger results will be getting by using the computerized diagnosis method to point the cancer cells in the colon and rectal regions of the pathological record to note down. The overall system speed is increased by the attentiveness of the particular target area by using the samples of patches. A well-organized system for the diagnosis will rapidly slow down the estimated price and it also is registered in a detached implementation to rescue the consulting people staying.	In this case, a unique cancer cell arrangement is structured and this will find the targeted area correctly and perfectly in relation according to neural networks using convolutional. Then using the deep neural networks process the final patch regions are picked up.

(*continued*)

Table 1. (*continued*)

Ref	Year	Inference	Design Methodology
23	**2020**	In this paper, the effects show off that a conditional GAN is having that the capacity to examine the nice illustration beginning stage cancer cells to suggest it will be represented numerically and pick out the degree of the record of cancer cell identification. So these kinds of approaches may be carried out with tone-of-a-kind varieties of cancer cells. So enhancing and modifying the present-day most cancers images are in each health care clinic and studies for comparing most cancers traits and also it will enhance most cancers records.	The type of GAN called Conditional GAN specifies cancer cell areas and then the complete technique is calculated by WSI images and tissues of biochip colon and rectal cells of samples.
24	**2020**	The trouble of finding the prognostic factor to detect and separate H&E-samples records of colorectal most cancers and an answer primarily based totally on a deep convolutional neural community changed into the present. The overall created machine gave an end result with the high-quality common intersection over union (IOU) for TB of 0.11, IOU for non-TB of 0.86 and because of this that IOU of 0.49 and weighted IOU of 0.83 resulted. In the end, the designed machine works under the belief that the primary cancer cells in the first stage changed into known ones.	An easily recognizable prognostic factor in H&E images by exhibiting numerous deep learning frameworks structured for recognizing a collection of pixel images and the planned system has a new CNN containing convolution filtrate with more elements of conditions.
25	**2015**	A CNN-based technique with a fully automatic deep learning-based method is used by pathologists in the detection of lung cancer diagnosis in whole slide Histopathological images. After that, the two CNN architectures VGG16 and ResNet50 were compared. VGG16 shows higher AUC and patch classification accuracy. For further improvement classification accuracy increases in training set size, by adding image augmentation and stain normalization.	It depicts a fully automatic method for lung cancer detection in whole slide images of lung tissue samples and the process is carried out on an image patch level using a convolutional neural network (CNN). Two CNN architectures VGG16 and ResNet50 CNN are formulated.

(*continued*)

Table 1. (*continued*)

Ref	Year	Inference	Design Methodology
26	**2016**	In this study, deep learning techniques for breast cancer sub-types classification was considered. ResNets as deeper and wider sparse networks are used to find the larger and more complex datasets in the cancer database. The inceptions with factorization and ResNets with deeper layers are good enough for image classification. It is also noted that deep ResNet models were more sensitive and reliable than Inception in all tested cancer data sets. Finally, when compared with existing methods, the ResNet frameworks achieve 99.8%, 98.7%, 94.8%, and 96.4% accuracy for four cancer types, two main breast cancer types, benign and malignant related sub- types were able to examine Histopathological images acquired by different imaging devices with different magnification levels.	In this analysis fine-tuned pre-trained deep neural networks ResNet V1 50 and ResNet V2 152 were used to distinguish between different cancer types.
27	**2021**	A reinforcement model of the community to locate the record over pathological images and to construct the warmth map that could spotlight the cancer cell location overlaying the warmth map era approach and function distributing approach of absolutely convolutional neural networks (CNN) to stability the precision and speed of finding the cancer cells location finding is produced. After the functions are derived from the warmth maps which can be incorporated into a conventional device gaining knowledge of a set of rules for the WSI-degree validation. This technique attains more overall performance of 97 percent precision at the cervical most cancers WSI records, additionally better and accountable. The mixed set of rules did fine outcomes at the WSI category undertaking of cervical cancers.	An approach combining both the AI types to recognize the speedy evaluation of cervical cancers Whole sliding records have constructed the usage of a susceptible observation method for educating the network. It is confirmed over the viability planned of the version on open records.

(*continued*)

Table 1. (*continued*)

Ref	Year	Inference	Design Methodology
28	**2020**	This type of precise system will give better results with fewer pathological records of images. Then for investigation and prognosis of cancer cells, segmenting the tissues of cancer cells is the very first important thing in the method. But this will rapidly show some disadvantages in the case of maintaining the precision of the final results. The instructed system will attain a performance speed of 94.35 percent and verification precision of 93.9 percent with the well-organized one with fewer sets of records.	For a faster and more precise system here part of a convolutional network that is network architecture u-net is used for segmenting the cancer cells of part over pathological images of the record and it is built moreover it is fully comprised of convolutional layers for image analysis.
29	**2019**	A pathological record for tissue has taken over the different algorithms and came with the accuracy of 99% of training 60:40 to draw architecture. Then it will separate the cancer cells and noncancer cells. By the end of the results if the cancer tissues are found. Then the segmented area of the region was executed on the image that was used for testing. The algorithm used will give the best adaptive algorithm than the clustering one. The mathematical record shows that the ConvNet for tissue differentiation in relation to the adaptive heuristic search algorithm for classification gives perfect results with a precision of 99 percent.	The differentiation of pathological image records is separated between cancer tissue and non-cancer tissues using the SVM classifier and ConvNet. For the segmentation of the histopathological images adaptive heuristic search algorithm and clustering problems are used.

(*continued*)

Table 1. (*continued*)

Ref	Year	Inference	Design Methodology
30	**2018**	The designed method consists of two stages, deep learning techniques to find the available tumor regions in the WSI, and the other one to find the result from the previous one, from that stage every information is downloaded to find the samples that are good or bad. An innovative patch of ConvNet with twelve layers to create the tissue-affected region cover is created. And then extract to classify the WSI image into a normal one or a malignant one. Overall, this finding gave a perfect AUC of 0.94 over the previous AUC of 0.925. The achievement will be again raised for a best better framework in the future.	The deep model network is constructed and elaborated to organize mild and malignant tissues in pathological records of fluid glands. A new AI method of learning techniques establishes a ConvNet of minimum need 64x64x3 aid record with twelve complex layers with pooling of maximum layers and rectified activation function is designed.
31	**2019**	This method has been designed for the investigation of ductal carcinoma images. Moreover, this area of finding is that one almost has a better relationship with the WSI image scanners. Making deep pathological records openly to be had will offer a breeding floor for the improvement of the latest record evaluation algorithms which decorate the objectivity of techniques and enhance first-class computerized analysis and prediction.	A general review of the samples is digitized with the observation of various processing methods using the pathological images. The approach starts with the investigation of those processed samples for computerized treatment and prediction of ductal carcinoma.

(*continued*)

Table 1. (*continued*)

Ref	Year	Inference	Design Methodology
32	**2021**	This framework is a powerful computerized method for the portion of melanin withinside the pores and skin pathologic record pix to rank and find the severe stage of tissue and the approach can supply excellent detection overall performance on pathological pix, in which the heritage is complicated and has a comparable look to the leading edge.	This technique has various levels in the pathological record of the skin. This technique uses the CLAHE rule set for image improvement with two side process. Preliminary segmentation is performed through a set of Fuzzy C-methods and for the end observation results a recursive neighborhood rule set is performed.
33	**2020**	The rule aims at nuclei finding and the texture elaborators explained in the present function are registered in the malignant cells. At last, after all the experiments using the support vector algorithms over 98.9 percent record of the images were organized and 99.6 percent were by random forest. So the computerized investigation of images is a cooperative one in the investigation mainly in the case of mainstream and especially in the region of brains.	Brain tumor tissues are classified using their own detection image investigation is created and the textures were derived.

Bibliography

1. B. Ehteshami Bejnordi et al., "Automated Detection of DCIS in Whole-Slide H&E-Stained Breast Histopathology Images," IEEE Trans. Med. Imaging, vol. 35, no. 9, pp. 2141–2150, 2016, doi: https://doi.org/10.1109/TMI.2016.2550620.
2. G. Logambal and V. Saravanan, "Detection and Segmentation in Histopathological Images," 2015 Glob. Conf. Commun. Technol., no. Gcct, pp. 128–132, 2015.
3. J. Foran, D; Yang L; Tuzel, O; Chen, W; Hu, J; Kurc, T; Ferreira, R; Saltz, "A caGRID-ENABLED, LEARNING BASED IMAGE SEGMENTATION METHOD FOR HISTOPATHOLOGY SPECIMENS The Cancer Institute of New Jersey, UMDNJ-RWJMS, Piscataway, NJ 08854 Department of Computer Science, Rutgers University, Piscataway, NJ 08854 Center for Compre," Proc IEEE Int Symp Biomed Imaging, pp. 1306–1309, 2009.
4. P. Bándi et al., "From Detection of Individual Metastases to Classification of Lymph Node Status at the Patient Level: The CAMELYON17 Challenge," IEEE Trans. Med. Imaging, vol. 38, no. 2, pp. 550–560, 2019, doi: https://doi.org/10.1109/TMI.2018.2867350.
5. M. F. A. Fauzi, W. Chen, D. Knight, H. Hampel, W. L. Frankel, and M. N. Gurcan, "Tumor Budding Detection system in Whole Slide Pathology Images," J. Med. Syst., vol. 44, no. 2, Feb. 2020, doi: https://doi.org/10.1007/s10916-019-1515- y.
6. M. Veta, J. P. W. Pluim, P. J. Van Diest, and M. A. Viergever, "Breast cancer histopathology image analysis: A review," IEEE Trans. Biomed. Eng., vol. 61, no. 5, pp. 1400–1411, 2014, doi: https://doi.org/10.1109/TBME.2014.2303852.
7. J. Ke, Y. Shen, Y. Guo, and X. Liang, "Fast Tumor Detector in Whole-Slide Image with Dynamic Programing Based Monte Carlo Sampling," Proc. - Int. Conf. Image Process. ICIP, vol. 2020-October, pp. 2471–2475, 2020, doi: https://doi.org/10.1109/ICIP40778.2020.9190987.
8. X. Zhang, W. Liu, and S. Zhang, "Mining histopathological images via hashing-based scalable image retrieval," 2014 IEEE 11th Int. Symp. Biomed. Imaging, ISBI 2014, pp. 1111–1114, 2014, doi: https://doi.org/10.1109/isbi.2014.6868069.
9. M. Dabass, R. Vig, and S. Vashisth, "Review of histopathological image segmentation via current deep learning approaches," 2018 4th Int. Conf. Comput. Commun. Autom. ICCCA 2018, no. 2, pp. 1–6, 2018, doi: https://doi.org/10.1109/CCAA.2018.8777616.
10. K. Gündüz, A. Albayrak, G. Bilgin, and M. E. Karslıgil, "Histopatolojik Görüntülerde Tümörlü Bölgelerin Evri ¸ simsel Sinir A ˘ glarıyla Sınıflandırılması Classification of Tumor Regions in Histopathological Images Using Convolutional Neural Networks," pp. 11–14.
11. M. J. Richardson and J. D. Wiltshire, "Processing Techniques," The Hologram, pp. 117–151, 2017, doi: https://doi.org/10.1002/9781119088929.ch6.
12. S. Khan, "Tumor Images and Analyzing its Textual Features," Icces, no. Icces, pp. 879–884, 2017.
13. S. A. F. Jahromi, A. A. Khani, H. O. Shahreza, M. S. Baghshah, and H. Behroozi, "A Deep Learning Framework for Viable Tumor Burden Estimation," 6th Iran. Conf. Signal Process. Intell. Syst. ICSPIS 2020, 2020, doi: https://doi.org/10.1109/ICSPIS51611.2020.9349569.
14. M. F. Jamaluddin, M. F. A. Fauzi, and F. S. Abas, "Tumor detection and whole slide classification of H&E lymph node images using convolutional neural network," Proc. 2017 IEEE Int. Conf. Signal Image Process. Appl. ICSIPA 2017, pp. 90–95, 2017, doi: https://doi.org/10.1109/ICSIPA.2017.8120585.
15. G. Corredor, J. D. Garcia-Arteaga, V. Arias, and E. Romero, "Learning basal cell carcinoma patterns by fusing pathologists' wsi navigations and graph-based centrality features," Proc. - Int. Symp. Biomed. Imaging, vol. 2019- April, no. Isbi, pp. 910–913, 2019, doi: https://doi.org/10.1109/ISBI.2019.8759570.

16. J. Han, D. V. Shin, G. L. Arthur, and C. R. Shyu, "Multi-resolution tile-based follicle detection using color and textural information of follicular lymphoma IHC slides," 2010 IEEE Int. Conf. Bioinforma. Biomed. Work. BIBMW 2010, pp. 866–867, 2010, doi: https://doi.org/10.1109/BIBMW.2010.5703949.
17. M. Matkoˇ, M. Matkošari´c, M. Russo, M. Stella, and M. Sikora, "CNN-based Method for Lung Cancer Detection in Whole Slide Histopathology Images."
18. P. Naylor, M. Laé, F. Reyal, and T. Walter, "Segmentation of Nuclei in Histopathology Images by Deep Regression of the Distance Map," IEEE Trans. Med. Imaging, vol. 38, no. 2, pp. 448–459, 2019, doi: https://doi.org/10.1109/TMI.2018.2865709.
19. K. Das, S. Conjeti, J. Chatterjee, and D. Sheet, "Detection of Breast Cancer from Whole Slide Histopathological Images Using Deep Multiple Instance CNN," IEEE Access, vol. 8, pp. 213502–213511, 2020, doi: https://doi.org/10.1109/ACCESS.2020.3040106.
20. S. Stenman et al., "Antibody Supervised Training of a Deep Learning Based Algorithm for Leukocyte Segmentation in Papillary Thyroid Carcinoma," IEEE J. Biomed. Heal. Informatics, vol. 25, no. 2, pp. 422–428, 2021, doi: https://doi.org/10.1109/JBHI.2020.2994970.
21. M. Robin, J. John, and A. Ravikumar, "Breast Tumor Segmentation using U-NET," Proc. - 5th Int. Conf. Comput. Methodol. Commun. ICCMC 2021, no. Iccmc, pp. 1164–1167, 2021, doi: https://doi.org/10.1109/ICCMC51019.2021.9418447.
22. L. Tchikindas, R. Sparks, J. Bacon, D. Ellison, A. R. Judkins, and A. Madabhushi, "Segmentation of nodular medulloblastoma using a random walker and hierarchical normalized cuts," 2011 IEEE 37th Annu. Northeast Bioeng. Conf. NEBEC 2011, pp. 4–5, 2011, doi: https://doi.org/10.1109/NEBC.2011.5778640.
23. A. Abdelli, R. Saouli, K. Djemal, and I. Youkana, "Combined Datasets for Breast Cancer Grading Based on Multi- CNN Architectures," 2020 10th Int. Conf. Image Process. Theory, Tools Appl. IPTA 2020, 2020, doi: https://doi.org/10.1109/IPTA50016.2020.9286653.
24. F. Siddiqui, S. Gupta, S. Dubey, S. Murtuza, and A. Jain, "Classification and diagnosis of invasive ductal carcinoma using deep learning," Proc. Conflu. 2020 - 10th Int. Conf. Cloud Comput. Data Sci. Eng., pp. 242–247, 2020, doi: https://doi.org/10.1109/Confluence47617.2020.9058077.
25. P. J. Ray, S. Priya, and T. A. Kumar, "Nuclear segmentation for skin cancer diagnosis from histopathological images," Glob. Conf. Commun. Technol. GCCT 2015, no. Gcct, pp. 397–401, 2015, doi: https://doi.org/10.1109/GCCT.2015.7342692.
26. K. Fukuma, V. B. Surya Prasath, H. Kawanaka, B. J. Aronow, and H. Takase, "A study on feature extraction and disease stage classification for glioma pathology images," 2016 IEEE Int. Conf. Fuzzy Syst. FUZZ-IEEE 2016, pp. 2150–2156, 2016, doi: https://doi.org/10.1109/FUZZ-IEEE.2016.7737958.
27. D. Krijgsman et al., "Quantitative Whole Slide Assessment of Tumor-Infiltrating CD8-Positive Lymphocytes in ER-Positive Breast Cancer in Relation to Clinical Outcome," IEEE J. Biomed. Heal. Informatics, vol. 25, no. 2, pp. 381–392, 2021, doi: https://doi.org/10.1109/JBHI.2020.3003475.
28. Q. D. Vu, K. Kim, and J. T. Kwak, "Unsupervised Tumor Characterization via Conditional Generative Adversarial Networks," IEEE J. Biomed. Heal. Informatics, vol. 25, no. 2, pp. 348–357, 2021, doi: https://doi.org/10.1109/JBHI.2020.2993560.
29. M. Saric, M. Russo, M. Stella, and M. Sikora, "CNN-based Method for Lung Cancer Detection in Whole Slide Histopathology Images," 2019 4th Int. Conf. Smart Sustain. Technol. Split. 2019, pp. 14–17, 2019, doi: https://doi.org/10.23919/SpliTech.2019.8783041.
30. S. Razavi et al., "An Automated and Accurate Methodology to Assess Ki-67 Labeling Index of Immunohistochemical Staining Images of Breast Cancer Tissues," Int. Conf. Syst. Signals, Image Process., vol. 2018-June, 2018, doi: https://doi.org/10.1109/IWSSIP.2018.8439184.

31. F. Xing, T. C. Cornish, T. Bennett, D. Ghosh, and L. Yang, "Pixel-to-Pixel Learning with Weak Supervision for Single-Stage Nucleus Recognition in Ki67 Images," IEEE Trans. Biomed. Eng., vol. 66, no. 11, pp. 3088–3097, 2019, doi: https://doi.org/10.1109/TBME.2019.2900378.
32. R. Deng et al., "Map3D: Registration-Based Multi-Object Tracking on 3D Serial Whole Slide Images," IEEE Trans. Med. Imaging, vol. 40, no. 7, pp. 1924–1933, 2021, doi: https://doi.org/10.1109/TMI.2021.3069154.
33. M. H. Masoudi and M. Mikaeili, "Diagnosis of Hodgkin's disease by identifying Reed-Sternberg cell nuclei in histopathological images of lymph nodes stained with Hematoxylin and Eosin," 27th Natl. 5th Int. Iran. Conf. Biomed. Eng. ICBME 2020, no. November, pp. 298–304, 2020, doi: https://doi.org/10.1109/ICBME51989.2020.9319460.
34. Q. Qi et al., "Curriculum Feature Alignment Domain Adaptation for Epithelium-Stroma Classification in Histopathological Images," IEEE J. Biomed. Heal. Informatics, vol. 25, no. 4, pp. 1163–1172, 2021, doi: https://doi.org/10.1109/JBHI.2020.3021558.
35. U. Qidwai and M. Sadia, "Color-based Fuzzy Classifier for automated detection of cancerous cells in histopathological analysis," IECBES 2014, Conf. Proc. - 2014 IEEE Conf. Biomed. Eng. Sci. "Miri, Where Eng. Med. Biol. Humanit. Meet," no. December, pp. 103–108, 2014, doi: https://doi.org/10.1109/IECBES.2014.7047464.
36. H. Sharma, N. Zerbe, C. Boger, S. Wienert, O. Hellwig, and P. Hufnagl, "A Comparative Study of Cell Nuclei Attributed Relational Graphs for Knowledge Description and Categorization in Histopathological Gastric Cancer Whole Slide Images," Proc. - IEEE Symp. Comput. Med. Syst., vol. 2017-June, pp. 61–66, 2017, doi: https://doi.org/10.1109/CBMS.2017.25.
37. H. Su, F. Xing, and L. Yang, "Robust Cell Detection of Histopathological Brain Tumor Images Using Sparse Reconstruction and Adaptive Dictionary Selection," IEEE Trans. Med. Imaging, vol. 35, no. 6, pp. 1575–1586, 2016, doi: https://doi.org/10.1109/TMI.2016.2520502.
38. D. Tellez et al., "Whole-Slide Mitosis Detection in H&E Breast Histology Using PHH3 as a Reference to Train Distilled Stain-Invariant Convolutional Networks," IEEE Trans. Med. Imaging, vol. 37, no. 9, pp. 2126–2136, 2018, doi: https://doi.org/10.1109/TMI.2018.2820199.
39. S. Wang, D. M. Yang, R. Rong, X. Zhan, and G. Xiao, "Pathology Image Analysis Using Segmentation Deep Learning Algorithms," Am. J. Pathol., vol. 189, no. 9, pp. 1686–1698, 2019, doi: https://doi.org/10.1016/j.ajpath.2019.05.007.
40. Clinical Characteristics and Outcomes for Solitary Fibrous Tumor (SFT): A Single Center Experience October 15, 2015 https://doi.org/10.1371/journal.pone.0140362.
41. Fast and Accurate Tumor Segmentation of Histology Images Using Persistent Homology and Deep Convolutional Features April 2019 DOI:https://doi.org/10.1016/j.media.2019.03.014.