10.48047/jocaaa.2024.33.07.29

A Study of Machine Intelligence in Cancer Care: Classification Techniques Reviewed

Dr. Megha Goyal
Assistant Professor, Department of Computer Science and Engineering, Dronacharya College of Engineering, Gurugram, Haryana
megha.goel@ggnindia.dronacharya.info

Dr. Bipin Pandey
Associate Professor, Department of Computer Science & Engineering, Dronacharya Group of Institutions, Greater Noida, Uttar Pradesh
bipin.pandey@gnindia.dronacharya.info

Abstract

Cancer is the disease that kills people the most worldwide, with the highest death rate. Among the most common and deadly types of cancer are brain tumors, lung cancer, skin cancer, breast cancer, and many more. Millions of people die from these severe and often fatal illnesses. Thus, a computer-assisted, automatic approach for early-stage cancer diagnosis has to be proposed as a solution. The two main stages of cancer progression are benign, which happens early in the disease, and malignant, which develops later in the disease and is more advanced with a tendency to spread. This work investigates various machine learning (ML) and deep learning (DL) based cancer detection techniques. Based on a variety of methodologies, features, datasets, and accuracy measured with the suggested method, the study was carried out. In addition to recently published research, we have used a variety of cancer types, such as brain tumors, skin cancer, breast cancer, and lung cancer. A cutting-edge table was also employed in the study to compare the results of earlier and later investigations on cancer detection methods. Based on the examination of various work types in relation to their degree of correctness, the analysis and comparison were conducted.

Keywords: Cancer detection, Segmentation, Machine Learning, Deep Learning, Feature Extraction.

Introduction

When compared to a few decades ago, the incidence of cancer in Indian society is far higher today. What's the difference? Why are chronic diseases like cancer becoming so common around the world? Does it make a difference when people change their eating habits? When a scientist considers cancer as it currently exists in the human body, he or she is likely to have many questions [1-5].

One of the deadliest illnesses of the 21st century is cancer, whose incidence has been startlingly high. It is difficult to comprehend the severity of cancer, which ranks first or second in the world among 91 nations. In terms of causes of death, cancer is ranked 172nd out of 172. One in four people now face the risk of developing cancer at some point in their lifetime due to the rate at which new cases are being reported. While only 11 lakh new cases of cancer are reported in India annually, 14 million new cases are diagnosed globally. Cancer is defined as the uncontrolled proliferation of cells in the human body, which is the primary cause of the disease. Cancer can develop in any part of the body, and depending on the circumstances, it may or may not spread to nearby cells. In general, depending on the stage, it can be classified as either benign or malignant. The benign tumor or cancer is a type of cancer that is in its early stages and does not spread to other parts of the body. Malignant tumors, on the other hand, are extremely dangerous because they can spread to other parts of the body [6-10].

Cancer can be completely cured if detected at an early stage and treated appropriately; however, this is only possible if the disease is recognized at an early stage. As a result, developing a method that can automatically identify and segment cancerous tissue with high precision at an early stage is critical to ensuring that patients receive the most effective treatment possible. The vast majority of skin cancer cases are successfully treated and cured

10.48047/jocaaa.2024.33.07.29

through surgery. In a similar vein, radiation has been successful in treating and curing a number of people with thyroid and laryngeal cancer [11-12].

Similar to this, if detected in their early stages, many other types of cancer may be treated. For example, early-stage diagnosis accounts for about 70% of cases of breast cancer. As a result, there are numerous varieties of cancer that can impact different body parts. The challenge is that, since there is no one-size-fits-all cancer treatment, each of these malignancies needs to be treated differently. Certain cancer types have higher survival rates when detected early. Prostate, skin, testicular, breast, cervix, and colon cancers are among the six types of cancer that have a good prognosis. There is a problem in that different factors cause different types of cancer, so no single strategy can prevent them all [13-15].

This work reviews the existing and forthcoming literature on the identification and classification of different types of tumors using biomedical image datasets. A manuscript with the survey attached is given. Only validated and benchmarked datasets that were used to identify and classify various tumors were used in the research for this study. In addition, all forms of cancer are taken into account in this study, including those that affect the brain, gastrointestinal system, skin, lungs, breast, and neck. It is not exclusive to any particular kind of cancer. This study's analysis also focused on the different features, different approaches (such as deep learning and machine learning), datasets utilized, type of cancer, and accuracy of classification and segmentation.

The article is arranged as follows after that: The research materials and methods, such as dataset types, preprocessing, and classifier types, are covered in section 2. The study's results are compiled and conclusions are drawn in Section 3. In Section 3, the essential elements of the cancer detection and segmentation algorithms utilizing biomedical image datasets are deconstructed and showcased. A thorough analysis of the literature used to achieve the analysis and research goals is presented in the fourth section. The final section, section 5, contains the concluding remarks and the scope of work to come [16-20]

Material and Methods

Different forms of cancer can be identified and categorized using a variety of methods. Preprocessing techniques, feature extraction techniques, classification techniques, databases to be used, and the following procedures are the main ways that machine learning can be used to detect cancer. Figure 1 illustrates the feature extraction, preprocessing, database creation, and classification procedures used in the ML and DL approaches for the categorization and identification of the different cancer types.

Databases

Picture databases are significantly easier to find than other types of databases. Numerous databases are currently available for use in identifying various forms of cancer. With its focus on brain tumors and cancer, the BRATS dataset is among the most significant of all the benchmark datasets. The three most recent versions of this dataset that are currently available for use are BRATS 15, BRATS 16, and BRATS 2018[12]. This collection consists of three-dimensional representations of magnetic resonance imaging (MRI) scans from various patient age groups. The Lung Image Database Consortium is the organization in charge of collecting and conserving images.

Two open-source datasets that can be used to identify lung cancer are image collections from the Lung Image Database Consortium and the Image Database Resource Initiative (LIDC-IDRI). There are 244,617 lung images in this collection, all of which come from patients in different age groups [13]. One of the benchmark datasets used to try and detect breast cancer is the "Wisconsin Breast Cancer Database," or WBCD for short. There are 699 records of human breast tissue in this database. Complete-Field Digital Mammography, or FFDM for short, consists of 739 images in total, 412 of which are classified as malignant and 327 as benign [21-25].

ISIC, an acronym for "The International Skin Imaging Collaboration," is a publicly accessible and freely downloadable collection of images of skin lesions. This database functions as a reference. The constant acquisition of different types of visual sensors has resulted in a diversity of picture natures in this dataset. Both the nature and

10.48047/jocaaa.2024.33.07.29

the size of the images in the database are subject to change. More than 2,560,300 publicly accessible tagged images of skin disorders associated with Dement can be found in the Dement collection.PH2 dataset: A PH2 dataset of skin lesions has been created for research and benchmarking purposes. The generation of this dataset facilitated comparative study of thermoscopic image segmentation and classification techniques [26-30].

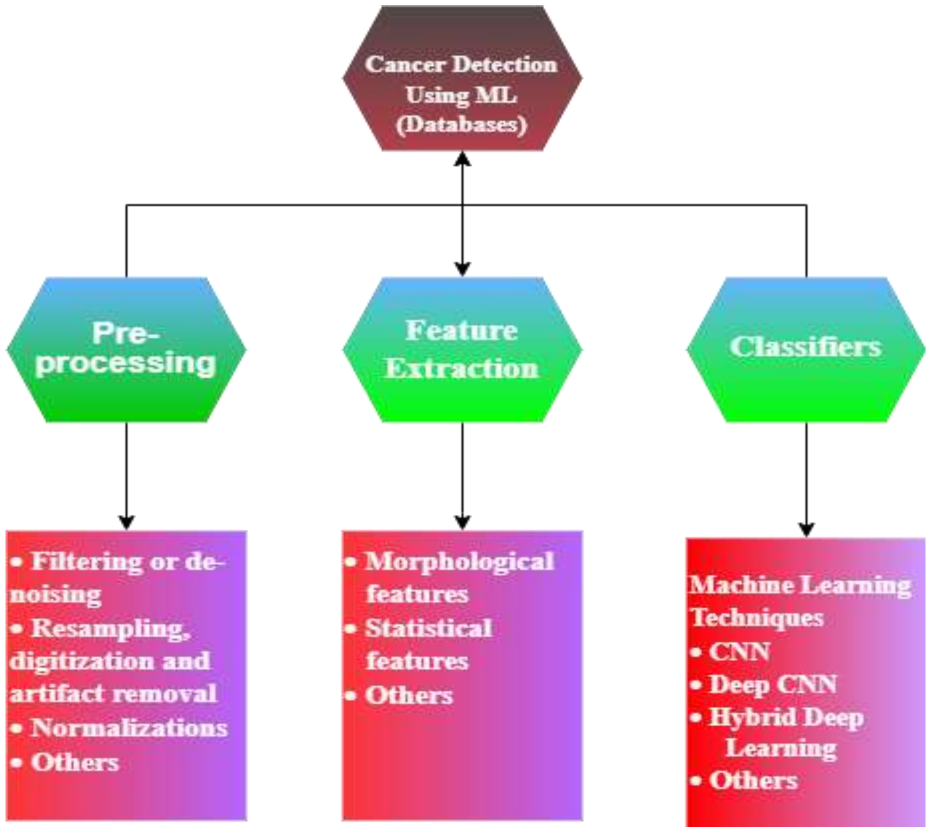

Fig.1: The basic steps involved in the detection of cancer using ML

Preprocessing

There are several steps involved in using the machine learning approach for image detection and segmentation, but the preprocessing step is one of the most important ones. The words "pre" and "processing," when combined, denote "before" processing; hence, the term "preprocessing". As a result, preprocessing describes the actions carried out prior to processing. Any raw data that was acquired could have been improperly formatted or contaminated by a variety of noises. These two problems are plausible. The data must first be transformed into the required or acceptable format before it can be processed. This is the most crucial requirement. Among the most popular preprocessing methods are filtering, also referred to as de-noising or noise reduction, smoothing, cropping, resizing, resampling, digitizing, artifact removal, normalizations, and a few more. Unorganized or noisy data may be the reason behind even the best machine learning classifier's poor performance. This is why preprocessing data in some way is required before supplying it to a neural or machine learning classifier [31-32].

Feature Extraction

The neural classifier must proceed to the feature extraction stage after the preprocessing stage. Both feature extraction and feature selection are extremely time-consuming processes that require a substantial investment of time, energy, and human resources. The neural classifier receives as input the features that were extracted from the previously processed data. Features are the specific and pertinent elements of the data that the classifier can use to

10.48047/jocaaa.2024.33.07.29

identify or classify. Variables should not be confused with features. As a result, depending on the features that are provided to the classifiers, their performance may vary. Depending on the dataset, the features may be selected automatically or by humans. The size or scope of the dataset can make feature extraction challenging, which could affect how well the classification performs. The dataset can be subjected to a wide range of additional feature extraction techniques. These consist of numerous other features as well as statistical, morphological, wavelet-based, color-based, local, and global features.

Classifiers

A multitude of tumors and disorders can be identified and categorized by using one of the many classifiers that are available. Both traditional machine learning-based classifiers and classifiers based on neural networks needed extracted features as input. Deep learning is an approach that can learn at a very deep feature level without requiring any features to be provided in the input. We might be able to resolve this problem and get around the feature extraction assignment by using deep learning, which learns at an extremely deep level. Deep learning models including generalized adverbial networks, long short-term memory networks (LSTM), convolutional neural networks (CNN), deep convolutional neural networks, natural language processing, and many more are widely used for detection and segmentation tasks.

Methodology

Figure 2 illustrates the suggested methodology for cancer detection and segmentation from image datasets using machine learning and deep learning. The first need is to get the image dataset from a trustworthy source; which source to use will depend on the kinds of cancer we want to find. The process of detecting cancer consists of three distinct steps: the segmentation step, the detection step, and the combination of the segmentation and detection steps. Neural network-based classifiers, deep learning models, or conventional machine learning can all be used to complete the classification or detection, depending on the specifics.

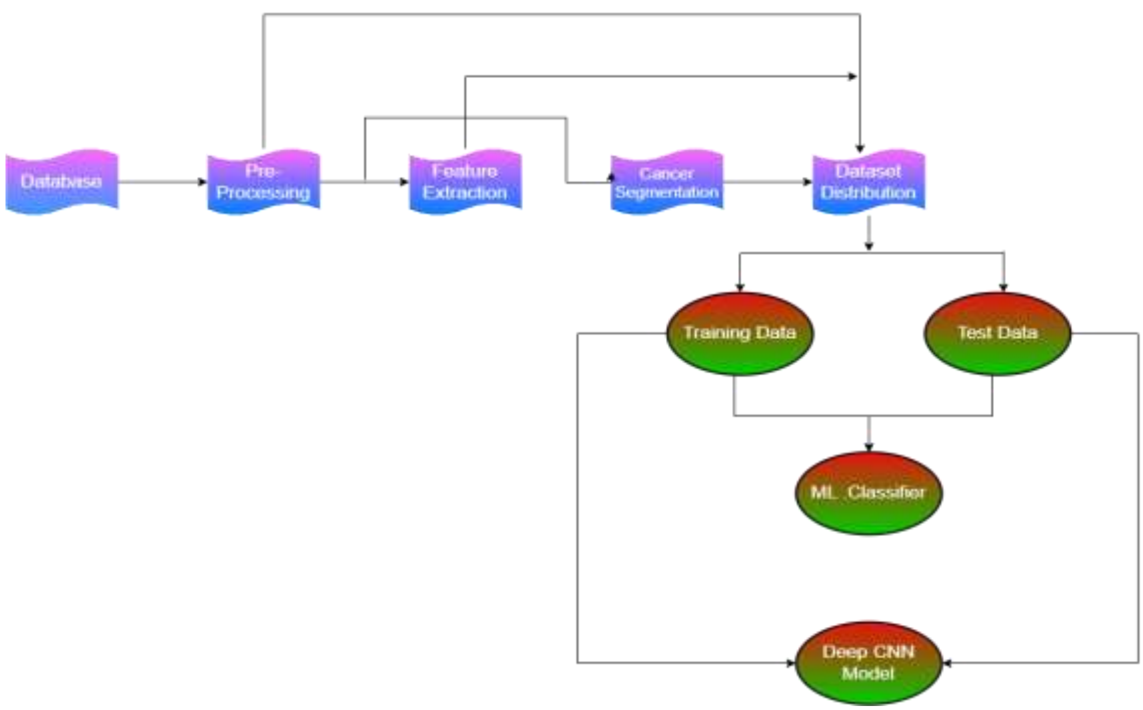

Fig.2: The overall methodology applied for the of cancer using ML and DL

10.48047/jocaaa.2024.33.07.29

Insufficient dataset size may lead us to believe that machine learning is the best method for diagnosing and categorizing cancer. The feature extraction methodology is only required once the detection ids have been determined using the machine learning approach. This is shown by the arrow line in the block. It has been shown that feature extraction is not necessary for the segmentation method, as indicated by the blue arrow line. The segmentation and detection process using ML approach involves the dataset, preprocessing, segmented images, dataset distribution (which separates the data into training and testing datasets), and, lastly, the suggested ML classifier. Deep learning classification and detection require a large dataset, but feature extraction methods do not. This is particularly true when using a CNN-based deep learning model. The two primary categories of the dataset are the training dataset and the test dataset. For the classifier to perform well, the training dataset needs to contain about 80% of the total data. Moreover, the test dataset is never used in the training phase because it's only use is to evaluate how well the trained model performs in real-world scenarios. The automated deep learning or machine learning method for cancer identification and segmentation processing may now be finished with the aid of the image dataset.

Discussion

Since cancer directly affects human lives, automated cancer identification is a very important task because even a small error could put patients' lives in jeopardy. For this reason, over the course of the last few decades, researchers have been applying machine learning and deep learning to develop techniques for automatically diagnosing various types of cancer. Several researchers have experimented with a variety of datasets and machine learning techniques to diagnose the various types of cancer. When employing ML and DL based techniques, the result has a classification accuracy ranging from 70 to 99 percent. The analysis's findings, which were based on the feature applied, the classifier employed, the dataset used, and the maximum classification accuracy attained, are displayed in Table 1.

As the table shows, the research used for the study came from recently published articles that were written between 2017 and 2022. By utilizing the K-means clustering approach, the authors in [15] were able to achieve the highest possible degree of classification accuracy—99.8 percent accurate. The HAM10000, a sizable dataset with multiple sources of thermoscopic pictures of common pigmented skin lesions, was utilized by them [16]. They conducted their investigation using this dataset. The researchers used a training picture dataset of 10,000 images to extract three different feature types: LBP, HOG, and BoVW. As a result, they achieved a 99.8% accuracy rate in identifying skin cancer using the K-means clustering classifier. The authors of [31], [30], and [21] have also classified cancer with the highest accuracy possible—98.266%, 98%, and 97.9%, respectively. In order to diagnose breast cancer, the authors used a hybrid dataset that combined the CBIS-DDSM, MIAS, and IN breast datasets with deep learning, from which [31] did not extract any features. They did not, however, assign a percentage of accuracy to the cancer's classification. The CNN deep learning approach was also utilized by the authors in [17] and [19] to identify cancer based on area under curve (AUC), which yielded results of 0.994 and 0.935, respectively.

The results obtained by [29] and [27] were the least accurate when compared to other methods, with classification accuracy of only 70 and 71 percent, respectively. At this level, the lowest accuracy possible was achieved. Using a dataset that combined ISIC and HAM10000, the authors of [29] employed a Deep CNN model without using any feature extraction methods. However, using texture, histogram, dynamics, and spatial data along with a CaPTk software, the authors of [27] were able to obtain 71% of the classification accuracy in order to identify cancer. All of the aforementioned qualities were used to achieve this. Using the largest dataset—27,815 and 23,907 photos, respectively—the authors in [19] and [28] were able to effectively finish their research. The authors in [23], [29], and [31] used large datasets created by integrating two or more datasets to achieve this. Without using any kind of features, many authors in [32], [31], [29], [28], and [18] have achieved accuracy of 98.266 percent, 97.08 percent, 70%, and 89.5 percent, respectively. Every author, apart from [29], who combined two large datasets to achieve good accuracy close to or above 90%, has done so. Parallel to this, every researcher—aside from the writers of [15], [24], and [30]—has previously employed deep learning models to distinguish between various forms of cancer. Almost every type of cancer has been investigated and studied, including skin cancer ([15], [28], [29]), lung cancer ([19], [21], [23], [32]), breast cancer ([17], [31]), brain cancer ([14], [24], [27], [30]), colorectal cancer ([18]), ([18]), and multiple cancer ([25],[26]).

10.48047/jocaaa.2024.33.07.29

Table 1: State-of-art table comparing the outcome of cancer detection using ML and DL techniques

Literature	Features	Technique	Dataset	Cancer Type	Best Accuracy
(Iqtidar et al., 2020) [15]	LBP, HOG, BoVW	K-Means Clustering	HAM 10000[16]	Skin	99.8%
(B.E. et al., 2017) [17]	various color and texture	CNN	399 whole-slide images	Breast	AUC: 0.994
(Yu et al., 2021) [18]	----	SSDL	13,111 whole slide images	Colorectal	93%
(Noorbakhsh et al., 2019) [19]	Quantitative Pathology	CNN	27,815 (TCGA) [20]	Pan or lung	AUCs > 0.935
(Saric et al., 2019) [21]	ROI	CNN	ACDC@LUNGHP [22]	Lung	97.9%
(K.-H. Yu et al., 2020) [23]	Morphological patterns	CNN	TCGA and ICGC	Lung	90%
(Rathore et al., 2018[14]	Intensity-based	Brain-Captk	BraTS'15	Brain	89.92%
(Tang et al., 2019) [24]	Texture based	ML	TCIA	Brain	84%
(Vu et al., 2019) [25]	Patch-level statistical and morphological	Deep CNN	MICCAI 2017	Lung, throat, Brain, etc.	81%
(Davatzikos et al., 2018) [26]	Texture, histogram, dynamics, spatial	CaPTk	Case-Control dataset	brain, breast, and lung	89.92%
(Fathi Kazerooni et al., 2020) [27]	Local, Regional, and global imaging patterns	CaPTk	Canicing Imaging Phenomics	Brain	71%
(Hasan et al., 2019) [28]		CNN	23,907 images from ISIC Archive	Skin	89.5%
(NEEMA M et al., 2020) [29]		Deep CNN	ISIC, HAM10000	Skin	70%
(Virupakshappa & Amarapur, 2020) [30]	MLWD, GLCM, GMI	AANN	BRATS 2015	Brain	98%
(Sannasi Chakravarthy & Rajaguru, 2022) [31]		ICS-ELM	CBIS-DDSM, MIAS, and IN breast	Breast	98.266%
(Ruan et al., 2022) [32]		DL based algorithm	1984 lung cancer CT scans	Lung	97.08%

Abbreviations: NV- Navye Bayes, SVM - Support Vector Machine, CNN - Convolutional Neural Network, GLCM - Gray Level Co-Occurrence Matrix, SL - Supervised Learning, DL - Deep Learning, SSDL - Semi Supervised Deep Learning, LBP - Local Binary Patterns, HOG - Histogram of Oriented Gradients, BoVW -Bag Of Visual Words, ROI - Regions Of Interest, TCIA - The Cancer Imaging Archive, TCGA - The Cancer Genome Atlas, Captk - Cancer Imaging Phenomics Toolkit, AANN - Adaptive Artificial Neural Network, Multi-Level wavelet, decomposition, MLWD - GMI -

10.48047/jocaaa.2024.33.07.29

Gabor and moment invariant, ICS-ELM - Extreme Learning Machine Optimized using a Simple Crow-Search Algorithm, CBIS-DDSM - Curated Breast Imaging Subset, MIAS - Mammographic Image Analysis Society, ACDC@LUNGHP - Automatic Cancer Detection and Classification in Whole-slide Lung Histopathology

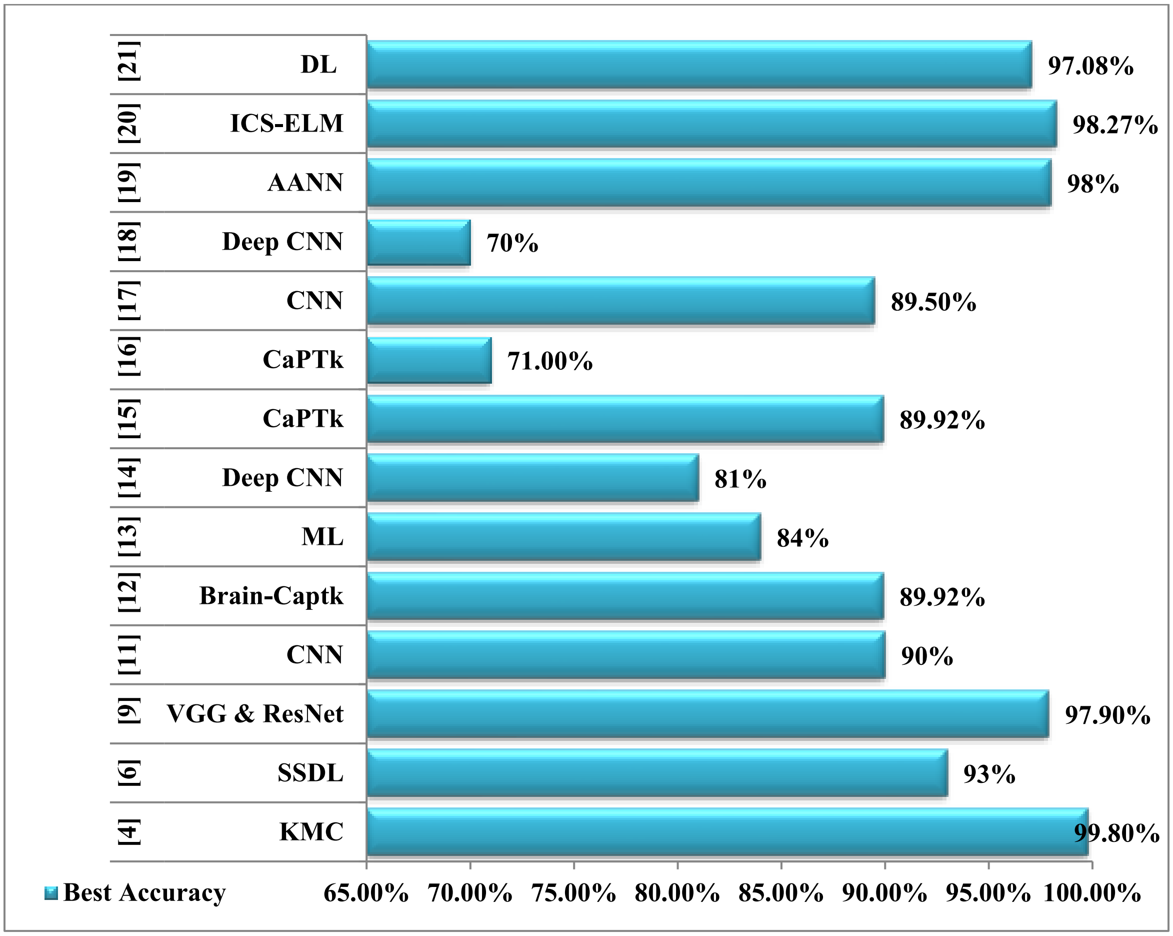

Fig.3: The comparative visualization of the accuracy of the cancer detection techniques

The analysis is shown in Figure 3 as a bar graph that contrasts the highest accuracy with the literature. The graph displays the highest accuracy's comparison to earlier studies. To preserve homogeneity, we have not incorporated the detection performance measured by AUC [17] and [19] into the analysis procedure. After conducting research on various tumor types and analyzing the data using ML and DL techniques, we arrived at the following conclusions:

1. Classification and segmentation accuracy could be further enhanced.

2. The collection ought to contain a higher overall count of pictures.

3. Large-scale medical datasets can be produced via the Generative Adversarial Network (GAN).

4. To diagnose and segment cancer, a hybrid deep learning model must be used, as this could increase the classifier's effectiveness.

5. It is feasible to develop a real-time, automated cancer detection system that is fast and precise.

10.48047/jocaaa.2024.33.07.29

Conclusion

As part of this investigation, we examined several techniques for identifying cancer using information from biomedical imaging. Nearly every type of cancer was included in this study, including cancers of the skin, breast, lungs, brain, colorectal, head and neck, and throat. This study incorporates work that was recently published, especially in the last five years, from 2017 to 2022. Our results show that the researchers used a variety of ML and DL algorithms, each with a distinct set of properties, to increase the detection accuracy. We conclude that good classification accuracy can be achieved without a large number of features and deep learning models based on the observations. By using as few features as possible, it is possible to diagnose cancer with high accuracy and a successful outcome using biomedical images and the best available classifier.

We hope to use hybrid deep learning models and large datasets in the future to try and further improve the accuracy and efficiency of cancer diagnosis. Additionally, we may use the GAN technique to generate a large number of cancer datasets in order to accurately train the classifier and provide accurate results.

References

[1] A. B. Nassif, M. A. Talib, Q. Nasir, Y. Afadar, and O. Elgendy, "Breast cancer detection using artificial intelligence techniques: A systematic literature review," *Artif. Intell. Med.*, vol. 127, p. 102276, May 2022, doi: 10.1016/j.artmed.2022.102276.

[2] J. Ferlay *et al.*, "Estimating the global cancer incidence and mortality in 2018: GLOBOCAN sources and methods," *Int. J. Cancer*, vol. 144, no. 8, pp. 1941–1953, 2019, doi: 10.1002/ijc.31937.

[3] F. Bray, J. Ferlay, I. Soerjomataram, R. L. Siegel, L. A. Torre, and A. Jemal, "Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries," *CA. Cancer J. Clin.*, vol. 68, no. 6, pp. 394–424, 2018, doi: 10.3322/caac.21492.

[4] P. S. Roy and B. J. Saikia, "Cancer and cure: A critical analysis," *Indian J. Cancer*, vol. 53, no. 3, pp. 441–442, 2016, doi: 10.4103/0019-509X.200658.

[5] M. A. A. Hamid and N. A. Khan, "Investigation and Classification of MRI Brain Tumors Using Feature Extraction Technique," *J. Med. Biol. Eng.*, vol. 40, no. 2, pp. 307–317, 2020, doi: 10.1007/s40846-020-00510-1.

[6] S. Kumar, C. Dabas, and S. Godara, "Classification of Brain MRI Tumor Images: A Hybrid Approach," *Procedia Comput. Sci.*, vol. 122, pp. 510–517, 2017, doi: 10.1016/j.procs.2017.11.400.

[7] M. Hosseinzadeh, S. Salmani, and M. H. M. Ara, "Interferometric optical testing to discriminate benign and malignant brain tumors," *J. Photochem. Photobiol. B Biol.*, vol. 199, no. August, p. 111590, 2019, doi: 10.1016/j.jphotobiol.2019.111590.

[8] S. S. Han, M. S. Kim, W. Lim, G. H. Park, I. Park, and S. E. Chang, "Classification of the Clinical Images for Benign and Malignant Cutaneous Tumors Using a Deep Learning Algorithm," *J. Invest. Dermatol.*, vol. 138, no. 7, pp. 1529–1538, 2018, doi: 10.1016/j.jid.2018.01.028.

[9] S. E. Steck and E. A. Murphy, "Dietary patterns and cancer risk," *Nat. Rev. Cancer*, vol. 20, no. 2, pp. 125–138, 2020, doi: 10.1038/s41568-019-0227-4.

[10] vinod k ramani, "Analysis of Bloodstream Infections and Their Antibiotic Sensitivity Pattern (Pre- and Post-COVID Lockdown in an Indian Cancer Hospital): A Record-Based Retrospective Cohort Study," *Eurasian J. Med. Oncol.*, 2022, doi: 10.14744/ejmo.2022.18855.

[11] C. I. Owobu *et al.*, "Pattern of Cancer in Irrua Specialist Teaching Hospital," *Int. J. Trop. Dis. Heal.*, vol. 42, no. December 2020, pp. 14–21, 2021, doi: 10.9734/ijtdh/2021/v42i730468.

10.48047/jocaaa.2024.33.07.29

[12] A. Myronenko, “3D MRI brain tumor segmentation using autoencoder regularization,” *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 11384 LNCS, pp. 311–320, 2019, doi: 10.1007/978-3-030-11726-9_28.

[13] T. Saba, “Recent advancement in cancer detection using machine learning: Systematic survey of decades, comparisons and challenges,” *J. Infect. Public Health*, vol. 13, no. 9, pp. 1274–1289, 2020, doi: 10.1016/j.jiph.2020.06.033.

[14] S. Rathore *et al.*, “Brain Cancer imaging phenomics toolkit (brain-CaPTk): An interactive platform for quantitative analysis of glioblastoma,” *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 10670 LNCS, pp. 133–145, 2018, doi: 10.1007/978-3-319-75238-9_12.

[15] K. Iqtidar, A. Iqtidar, W. Ali, S. Aziz, and M. U. Khan, “Image Pattern Analysis towards Classification of Skin Cancer through Dermoscopic Images,” *Proc. - 2020 1st Int. Conf. Smart Syst. Emerg. Technol. SMART-TECH 2020*, no. January 2021, pp. 208–213, 2020, doi: 10.1109/SMART-TECH49988.2020.00055.

[16] P. Tschandl, C. Rosendahl, and H. Kittler, “The HAM10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions,” *Sci. Data*, vol. 5, no. 1, p. 180161, Dec. 2018, doi: 10.1038/sdata.2018.161.

[17] B. E. Bejnordi *et al.*, “Diagnostic Assessment of Deep Learning Algorithms for Detection of Lymph Node Metastases in Women With Breast Cancer,” *JAMA*, vol. 318, no. 22, p. 2199, Dec. 2017, doi: 10.1001/jama.2017.14585.

[18] G. Yu *et al.*, “Accurate recognition of colorectal cancer with semi-supervised deep learning on pathological images,” *Nat. Commun.*, vol. 12, no. 1, pp. 1–13, 2021, doi: 10.1038/s41467-021-26643-8.

[19] J. Noorbakhsh, S. Farahmand, M. Soltanieh-ha, S. Namburi, K. Zarringhalam, and J. H. Chuang, “Pan-cancer classifications of tumor histological images using deep learning,” *bioRxiv*, vol. 64, p. 715656, 2019, [Online]. Available: https://www.biorxiv.org/content/10.1101/715656v1.full.

[20] L. A. D. Cooper, E. G. Demicco, J. H. Saltz, R. T. Powell, A. Rao, and A. J. Lazar, “PanCancer insights from The Cancer Genome Atlas: the pathologist’s perspective,” *J. Pathol.*, vol. 244, no. 5, pp. 512–524, 2018, doi: 10.1002/path.5028.

[21] 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: 10.23919/SpliTech.2019.8783041.

[22] “Cancer Detection and Classification in Whole-slide Lung Histopathology,” Accessed: May 29, 2022. [Online]. Available: https://acdc-lunghp.grand-challenge.org/.

[23] K.-H. Yu *et al.*, “Classifying non-small cell lung cancer types and transcriptomic subtypes using convolutional neural networks,” *J. Am. Med. Informatics Assoc.*, vol. 27, no. 5, pp. 757–769, May 2020, doi: 10.1093/jamia/ocz230.

[24] T. T. Tang, J. A. Zawaski, K. N. Francis, A. A. Qutub, and M. W. Gaber, “Image-based Classification of Tumor Type and Growth Rate using Machine Learning: a preclinical study,” *Sci. Rep.*, vol. 9, no. 1, pp. 1–10, 2019, doi: 10.1038/s41598-019-48738-5.

[25] Q. D. Vu *et al.*, “Methods for segmentation and classification of digital microscopy tissue images,” *Front. Bioeng. Biotechnol.*, vol. 7, no. APR, 2019, doi: 10.3389/fbioe.2019.00053.

[26] C. Davatzikos *et al.*, “Cancer imaging phenomics toolkit: quantitative imaging analytics for precision diagnostics and predictive modeling of clinical outcome,” *J. Med. Imaging*, vol. 5, no. 01, p. 1, 2018, doi: 10.1117/1.jmi.5.1.011018.

[27] A. Fathi Kazerooni *et al.*, “Cancer Imaging Phenomics via CaPTk: Multi-Institutional Prediction of

10.48047/jocaaa.2024.33.07.29

Progression-Free Survival and Pattern of Recurrence in Glioblastoma," *JCO Clin. Cancer Informatics*, no. 4, pp. 234–244, 2020, doi: 10.1200/cci.19.00121.

[28] M. Hasan, S. Das Barman, S. Islam, and A. W. Reza, "Skin cancer detection using convolutional neural network," *ACM Int. Conf. Proceeding Ser.*, no. March 2020, pp. 254–258, 2019, doi: 10.1145/3330482.3330525.

[29] NEEMA M, A. S. NAIR, A. JOY, A. P. MENON, and A. HARIS, "SKIN LESION/CANCER DETECTION USING DEEP LEARNING," *Int. J. Appl. Eng. Res.*, vol. 15, no. 1, pp. 11–17, 2020.

[30] Virupakshappa and B. Amarapur, "Computer-aided diagnosis applied to MRI images of brain tumor using cognition based modified level set and optimized ANN classifier," *Multimed. Tools Appl.*, vol. 79, no. 5–6, pp. 3571–3599, Feb. 2020, doi: 10.1007/s11042-018-6176-1.

[31] S. R. Sannasi Chakravarthy and H. Rajaguru, "Automatic Detection and Classification of Mammograms Using Improved Extreme Learning Machine with Deep Learning," *IRBM*, vol. 43, no. 1, pp. 49–61, Feb. 2022, doi: 10.1016/j.irbm.2020.12.004.

[32] J. Ruan, Y. Meng, F. Zhao, H. Gu, L. He, and X. Gong, "Development of Deep Learning-based Automatic Scan Range Setting Model for Lung Cancer Screening Low-dose CT Imaging," *Acad. Radiol.*, Feb. 2022, doi: 10.1016/j.acra.2021.12.001.