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Recent advancement in cancer diagnosis using machine learning and deep learning techniques: A comprehensive review

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ABSTRACT

Being a second most cause of mortality worldwide, cancer has been identified as a perilous disease for human beings, where advance stage diagnosis may not help much in safeguarding patients from mortality. Thus, efforts to provide a sustainable architecture with proven cancer prevention estimate and provision for early diagnosis of cancer is the need of hours. Advent of machine learning methods enriched cancer diagnosis area with its overwhelmed efficiency & low error-rate then humans. A significant revolution has been witnessed in the development of machine learning & deep learning assisted system for segmentation & classification of various cancers during past decade. This research paper includes a review of various types of cancer detection via different data modalities using machine learning & deep learning-based methods along with different feature extraction techniques and benchmark datasets utilized in the recent six years studies. The focus of this study is to review, analyse, classify, and address the recent development in cancer detection and diagnosis of six types of cancers i.e., breast, lung, liver, skin, brain and pancreatic cancer, using machine learning & deep learning techniques. Various state-of-the-art technique are clustered into same group and results are examined through key performance indicators like accuracy, area under the curve, precision, sensitivity, dice score on benchmark datasets and concluded with future research work challenges.

1. Introduction

As per World Health Organization's (WHO) global health estimate (GHE)-2020, carried over 180 countries of the world, cause of deaths from all diseases has been categorized in three major categories i.e., "Communicable, maternal, perinatal and nutritional conditions", "Noncommunicable diseases" and "Injuries", recording mortality rate of 18.4%, 73.6% and 8.0% respectively. These categories consist of multiple sub categories, out of which, cumulative deaths reported from all cancer type (Noncommunicable diseases) is 16.8% worldwide, making it 2nd leading cause of death after cardiovascular diseases in individual sub category [1].

Cancer is a perilous disease in which the cells that are abnormal, are uncontrollably divides and try to destroy the body tissues, making it very dangerous and life-threatening for human's life. Cancer has been recognized as foremost cause of death worldwide due to its elevated mortality count (10 million) and incidence count (19.3 million) in year 2019 and as per International Agency of Research on Cancer (IARC) estimates, approximate incidence count & mortality count is expected to upsurge to 29.5 & 16.4 million respectively in the year 2040 [2]. Fig. 1A & 1B, represent the continent-wise current & future estimated growth of incidence & mortality count by all cancer types, identifying Asian countries as most affected region by cancer diseases. Cancer is also referred as tumor which must be detected or diagnosed in its initial stage to cure its patients correctly and timely manner. Most of the deaths reported worldwide by lung cancer (19%), followed by colon cancer (10%), stomach cancer (9%), breast cancer (7%), liver cancer (6%), pancreas cancer (5%), brain cancer (3%), skin cancer (1%) and so on [1].

In this research work, we have considered diagnosis of six types of cancer i.e., breast, lung, liver, skin, Brain and pancreatic cancer, to find out recent development in artificial intelligence (AI)-based method's in-vogue, specifically employed on medical diagnosis of different types of cancer. Brief information of different considered cancer types and machine learning (ML) & deep learning (DL) pipe lines for cancer detection have been described in this section.

Lung cancer, leading contributor in cancer mortalities, is instigated due to the progression of small abnormal tissue in lung called nodules. It

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is observed that 95% of the mortalities by lung cancer are of, above the age range of 50 years during the year 2019 [1]. There are two nodules types that can help in defining the tissues to be cancerous or non-cancerous, one is benign nodule which is non-cancerous and does not spread in other parts of the body and second one is malignant nodule which is cancerous and can spread quickly in other body parts [3]. Hence to avoid malignant nodule, the early treatment is required. Most likely modality used are computerized tomography (CT), positron emission tomography (PET), histopathology (HS) images and RNA Sequence [4,5].

Another deadly & gender specific cancer type is breast cancer, which may cause mortality in women. It is primarily caused by anomalous growth of breast tissues, and typically known as benign and malignant cell. It is very difficult to diagnose the patient with malignant cells in early stage due to low traceability of small sized tumor [6,7]. To identify such kind of cells, the advanced computer aided diagnosis (CAD) system are needed. Mammographic (MG) & ultrasound (US) images, RNA sequence, electronic health records (EHR), and sometimes thermographic image are frequently used data modalities for initial stage diagnosis of Breast cancer [8,9].

Liver cancer or hepatic cancer, mostly affects the human life as liver is the indispensable part of the human body. Various basic functions of the body are reliant upon it i.e., detoxification of the drugs, purification of blood & generation of proteins needed for blood. Most common liver cancer is hepatocellular carcinoma (HCC) [10]. As per WHO reports, 99% of the mortalities by liver cancer are of above the age of 30 years in the year 2019 [1]. Some of the risk factors related to liver cancer are –smoking, eating fatty food, taking alcohol etc. Mostly CT, US, magnetic resonance imaging (MRI), RNA Sequence and EHR types of modalities, are being used to detect liver cancer is its initial stages [11,12].

Pancreas cancer (PC) is a disease, which is developed by formation of malignant acinar and ductal cells the pancreatic tissue. It is a gland situated in front of spine & behind the stomach. Helping in digestion (exocrine) and regulating blood sugar (endocrine) are the two-prime job of this gland [13]. Diagnosis of PC is fruitful only if it is somehow detected in phase I or II only. Due to its location, deep down inside the abdomen, and asymptomatic nature, PC is tough to diagnose in its early stages. 93% of the mortalities by PC were of above the age range of 50 years in the year 2019 [1]. CT, PET, MRI, endoscopic ultrasound (EUS), RNA Sequence and EHR are the major modality used in early detection of Pancreas cancer [14,15].

Brain cancer, also referred as brain tumor, is an irregular growth of cells or mass in human brain. Observations indicated that cancer took up to brain cell from other part of body during its metastatic stage [16]. Not all masses created are cancerous. Brain tumor can be categorized in two parts, under low grade which grows lowly and high grade which affects blood supply in brain. Most common brain tumor, which affect adults mostly, is glioblastoma and the patients suffering from this have survival time of less than 5 years. 94% of the mortalities by brain cancer are of above the age of 15 years has been recorded in the year 2019 by WHO [1]. Mostly MRI and sometimes diffusion tensor imaging (DTI) & functional magnetic resonance imaging (FMRI) modalities are used for early diagnosis of brain cancer [17,18].

Skin cancer, rapidly growing diseases, develops due to the irregular spread of skin cells under the exposer of ultra violet (UV) radiation from sun mostly and may spread in other parts of the body [19]. This disease can also be categorized in two parts-melanoma, & non-melanoma. Melanoma type can be spotted as a dark spot on the skin and comes in the category of dangerous cancer [20]. It is seen that a small mole can be changed to big dark spot which results in skin cancer and it started taking the shape of itchiness, colour change and irregular edges. Observation indicated that 99% of the mortalities by skin cancer were of above the age of 30 years in the year 2019 [1]. Dermoscopic (DY) images is the typical modality used during early diagnosis of skin cancer [21,22].

The techniques to analyse medical data, either clinical records or medical images, are essentially required to reduce the mortality rate in order to detect the disease in its early stage [23]. It is not wrong to say that the medical data analysis plays significant role to identify different types of cancerous tissues in human body part. Many ML/DL-based techniques are available to detect and evaluate different human organ's abnormalities using different modalities like US, X-Rays, CT, PET, MRI, single-photon emission computerized tomography (SPECT), MG, HS, DY, EUS, RNA Sequence and Retinal imaging [24,25]. Typically ML methods are preferable in case of small sized dataset in hand, whereas DL methods are more preferable in case of large sized dataset in hand to work upon. Different imaging modalities utilize different principles underneath for identification of various physical quantities present in medical images. For example, CT uses the principle of energy of incident photons, PET utilizes principle of photons energy & its detection time, MRI uses different parameters of a radio frequency (RF) signal produced by the excited atoms and ultrasonography utilizes fundamental of acoustic echoes [26,27].

Various machine learning (ML) techniques have been used to detect various cancer types i.e. lung, brain, breast, skin, blood, hippocampus, pancreas, cardiac, colon cancer, hepatic vessel, spleen etc. [28] In general, medical data comprises of two data form, one is structured or low dimensional data, normally referred as EHR and another one is unstructured or high dimensional data, generally known as medical images [29]. Generally, ML techniques follows certain process flows to cater medical data analysis like pre-processing, feature-engineering, model-training, model-testing and prediction/classification as shown in Fig. 2.

Internal process flow among ML processes may look different in different medical data forms like, in case of medical images, which comprises of data-collection, segmentation, model training and at last

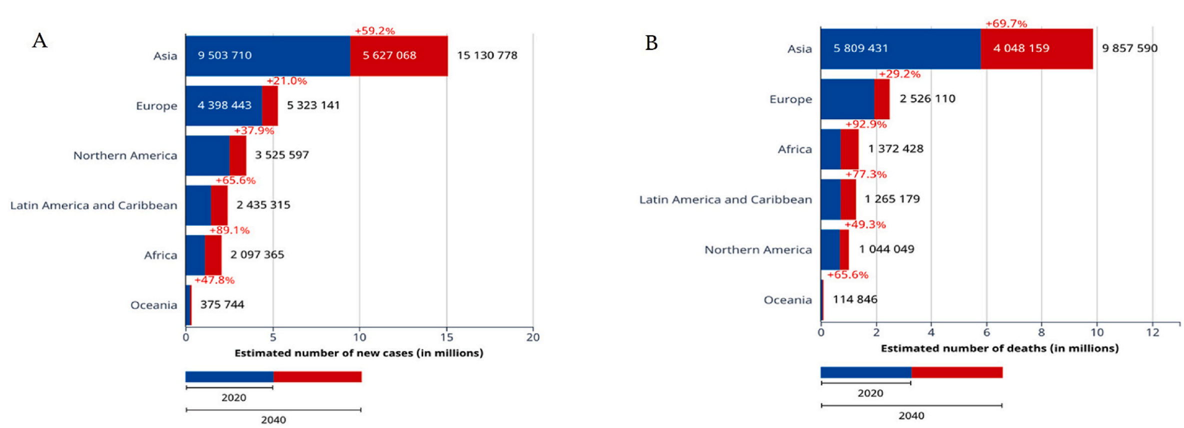

Fig. 1. Current & future state of (A) incidence and (B) mortality count by cancer disease.

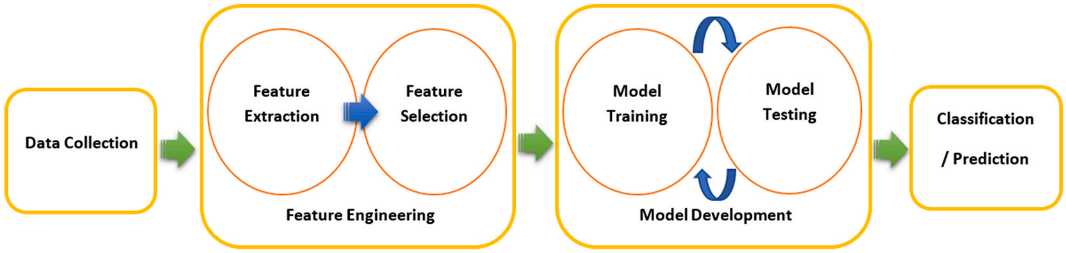

Fig. 2. Basic machine learning process flow.

classification process. Thus, ML pipeline for structured data will be totally different in comparison with ML pipeline for unstructured data as given in Fig. 3.

Image processing plays an important role in medical image analysis and is a critical part of image-based medical diagnosis. Medical image processing typically includes various steps like data acquisition, reconstruction, enhancements analysis & prediction task [26,30]. Data acquisition primarily deals with procurement of raw imaging data of different modalities i.e., CT, PET, MRI, US etc., from different sources, further this process also includes physical entity detection, preconditioning and digitization of acquired signals. After data acquisition, in the next phase image reconstruction is performed, which deals with forming of images from acquired raw data via mathematical processes [31]. These mathematical algorithms include various analytical methods i.e., filtered back projection (FBP), delay and sum (DAS) beamforming & Fourier transform (FT) and iterative methods i.e., maximum a posteriori (MAP), maximum likelihood expectation maximization (MLEM) & algebraic reconstruction (ARC) techniques. In the next phase image enhancement process is employed on constructed images to refine & transform images to enhance interpretability of physical entities present in image [32,33]. It is typically achieved by different contrast optimization, noise reduction, edge enhancement, artefacts elimination and image smoothening methods. Analysis step contain image registration, segmentation & quantification task as a whole, where registration process ensures proper alignment of multiple images of different modalities, image segmentation deals with partitioning of image into meaningful outlines of different material structures available in image and last quantification process is needed to discover characteristics of identified physical entities in image i.e., diameter, volume & composition of entity. Result of these steps led to improved accuracy & quality of medical findings. At the last step of medical image analysis, prediction step deals with training, validation & testing of different ML/DL-based algorithms over pre-processed image data to automate the task of disease diagnosis [9,34,35].

A lot of work has been carried out in the field of early-stage cancer diagnosis to minimize mortality rate due to cancer disease in the recent years and many researchers have presented their review or survey studies on cancer diagnosis using ML/DL-based methods so far. On investigation of various previously published review articles, it was observed that many of the review articles are focused on specific type of cancer diagnosis [34,36–38] and quite limited number of studies have targeted reviews of multiple types of cancer diagnosis [23,39–41]. One review article is observed to be quite impressive covering diagnosis of five cancer types using ML methods with exploration of almost all relevant analysis factors, but differs in types of covered cancer with respect to our review article [42].

Although all of the considered studies discussed and presented their findings & related information in a scientifically correct manner, however, not all of them considered many of the relevant factors related to analysis of cancer diagnosis using machine learning i.e., some of review articles have not considered presenting feature extraction techniques used along with ML/DL-based methods [23,34,37–41], some studies have not explored data modalities i.e., CT, MRI, US, PET, HER, Genomic sequence etc., in their literature [34,37,39,41], and some of the studies even haven't considered presenting classification accuracy parameter [38,40] as well as utilized datasets [37,38] information in their review articles.

Keeping in mind above issues, in this paper we tried to include most of the relevant analysis parameter needed to explore different ML/DL-based methodologies applied previously in the field of early cancer diagnosis, which may deliver some additional information in knowledgebase of novice researchers who are going to be benefited after reading this article. Analysis parameters considered in our study are ML/DL-based method utilized, feature extraction techniques employed, dataset hands on with, data modality used and classification accuracy received by applied methods and these parameters are extracted against diagnosis of six different cancer types named lung, brain, liver, breast, pancreas & skin cancer. Four former cancer types are leading cause of mortality worldwide and two later cancer types falls under rare type to cancers, whose incident rate is growing significantly. This study is advantageous for researchers who are both keen to research upon early cancer diagnosis using AI-enabled methods and are interested specifically on cancer types covered in the study. Furthermore, novice researchers may also be get benefitted by this paper as this study has explored significant amount of information relevant to cancer diagnosis using ML/DL-based methods. Researchers, working in diagnosis of cancer types other than considered in this study and looking for diagnosis methods other than ML/DL-based methods may find this study irrelevant to their subject domain, which could be considered as disadvantage of this study.

This paper is further subdivided into six main sections. Section 2 describes the scope & objective of this study, Section 3 provides description of cancer type-wise benchmark datasets used frequently in recent past by researcher, Section 4 presents literature selection

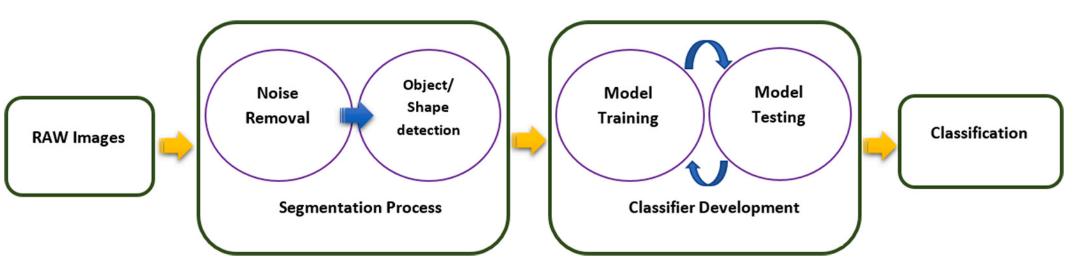

Fig. 3. Machine learning process flow for medical image data.

methodology adopted during this study, which is followed by cancer type-wise detailed literature survey along with respective analysis table, containing different parameter extracted from literatures considered during this study in Section 5. Section 6 includes analysis & discussion segment, where most frequently used ML & DL-based method, feature extraction techniques, data modalities and cancer type-wise most accurate methods using accuracy parameters are identified and presented as a result of analysis. Furthermore, this section also describes brief introduction of most frequently employed ML/DL-based methods and feature extraction methods along with challenges related to cancer diagnosis using ML/DL-based methods. At last, Section 7 summarizes this entire study and presents a conclusion in brief.

2. Scope and objective

Emergence of ML/DL-based methods have enriched cancer diagnosis field with its overwhelmed efficiency in computation of complex problem. Various types of cancer detection methods using ML/DL-based techniques have introduced a new research area for early detection of cancers. This review paper presents comprehensive survey & analysis of research done in past six years during 2016–2021 on ML/DL-based diagnosis of six different cancers types i.e., liver, lung, brain, breast, skin & pancreas cancer. Leading ML/DL-based methodology along with key feature extraction techniques utilized, benchmark datasets & data modalities employed and received classification accuracy by employed ML methods, were the focal point for analysis & review of this study.

3. Benchmark datasets

This section describes cancer type wise benchmark datasets utilized commonly for experimentation, comparisons and analysis of state-of-art ML techniques for different cancer detection & classification purpose. Further this section highlights their sources, training sets, test sets, key performance indicators (KPI's) in connection with cancer diagnosis including segmentation and classification as seen in Fig. 4.

3.1. *Lung cancer datasets*

3.1.1. *LIDC-IDRI*

It is an open-source database consisting of 2,44,527 annotated CT images of lung cancer screening of 1010 patients provided by Lung Images Database Consortium (LIDC). It is one the most commonly used dataset among researchers and personnel's working in lung cancer detection & diagnosis.

3.1.2. *Cancer genome atlas lung squamous cell carcinoma (TCGA-LUSC)*

This is open-source dataset of 36518 images of CT & PET modality from 37 patients. This dataset also provides genomic data of thousands of genes responsible for lung cancer using Genomic Data Commons (GDC) Data Portal.

3.1.3. *Lung nodule analysis 2016 (LUNA16)*

LUNA16 is a database of 888 annotated CT scans of 601 patient chest cavities from public dataset named LIDC-IDRI particularly provided for open challenge conducted during 2016 by Colin Jacobs & Team, Radboud University Medical Center, Nijmegen, The Netherlands, in search of best algorithm lung cancer detection.

3.1.4. *Programmed death-ligand 1 (PD-L1)*

This dataset is a collection of CT images of selected 939 patients out of 2094 patients with stage IV of non-small cell lung cancer (NSCLC) underwent PD-L1 staining and qualified on CT scan quality measures at West China Hospital of Sichuan University.

3.1.5. *Kaggle data science bowl 2017 challenge (KDSB17)*

KDSB17 dataset contains 2101 axial CT scans of hundreds of lung cancer patients, released in two stages (1595 in former & 506 in later stage) by Booz Allen and Kaggle team. This dataset is made up of patient's images provided by the National Cancer Institute (NCI) and utilized for open challenge for researchers & data science engineers looking for best algorithm contribution.

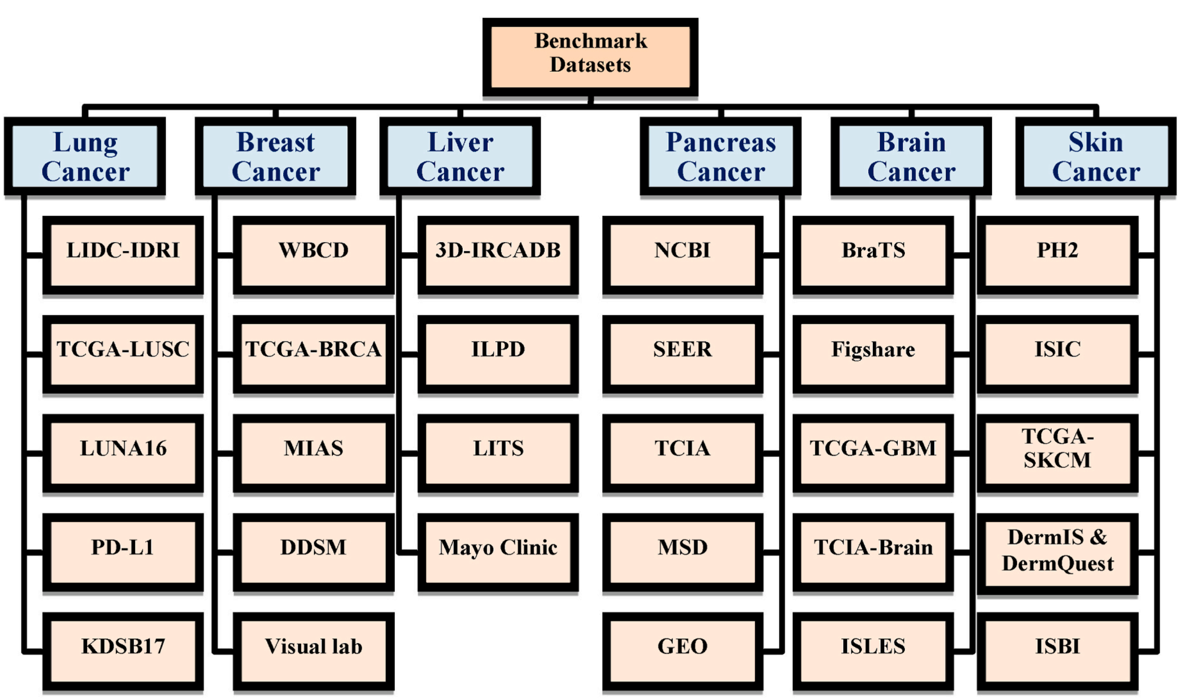

Fig. 4. Benchmark datasets.

3.2. Breast cancer datasets

3.2.1. Wisconsin breast cancer database (WBCD)

WBCD, most frequently employed public dataset in breast cancer research, is created by physician of University of Wisconsin Hospital – Madison named Dr. WIlliam H. Wolberg by extracting important features from fine needle aspirate (FNA) digital images of breast mass. It contains 569 instances of 32 extracted features and generally used for classification of breast cancer task by researchers.

3.2.2. Cancer genome atlas breast invasive carcinoma (TCGA-BRCA)

TCGA-BRCA is a public dataset comprising of 230,167 images of MG & MRI modalities from 139 breast cancer patients provided by The Cancer Imaging Archive (TCIA) group for research & experiment purpose. This dataset also has provision to provide genomic data of thousands of genes responsible for breast cancer using GDC Data Portal.

3.2.3. Mammographic image analysis society (MIAS)

MIAS, most commonly used dataset, is an open-source dataset having 322 digital mammogram films of 161 breast cancer patients with respective ground truth, which is collected from UK National Breast Screening Program by UK research groups.

3.2.4. Digital database for screening mammography (DDSM)

DDSM is also a public dataset for breast cancer research. It is having 2596 mammographic images with associated patient data like age, ACR breast density rating and image related information. Availability of ground truth with DDSM Dataset makes it suitable for benchmarking ML techniques for detection of breast cancer for researchers.

3.2.5. Visual laboratory database

This database is standard database for breast cancer detection having 1280 thermographic images of 64 participants (32 healthy and 32 with abnormalities). It is created by Fluminense Federal University in Rio de Janeiro, Brazil by taking 20 sequential thermal images from each participant.

3.3. Liver cancer datasets

3.3.1. 3D-image reconstruction for comparison of algorithm database (3D-IRCADB)

3D-IRCADB-01 is a collection of 3D images of CT modality from 20 liver cancer patients (10 male & 10 female). 75% of cases are with hepatic tumor and rest are healthy one. Dataset is having multiple additional information about patient's age, liver size, liver average density, making it a suitable choice to benchmark different machine learning based segmentation algorithm.

3.3.2. Indian liver patient dataset (ILPD)

ILPD is also a commonly used dataset for liver cancer detection publicly available in UCI machine learning repository. This data set consist of 583 instances (416 liver cancer patients & 167 healthy one) having 10 attributes. Data is collected from north east region of Andhra Pradesh-India and 441 male and 142 female patients participated in dataset development.

3.3.3. Liver tumor segmentation challenge (LITS)

LITS is a collection of contrast enhanced abdominal CT scans, provided during LITS challenge to motivate researchers to come up with automatic segmentation algorithm for liver lesions. It contains 200 CT scan of multiple liver patients, out of which 130 CT scans are reserved for algorithm training purpose and rest 70 CT scans are for testing purpose. Other variant, LITS 2018 is having 475 MRI scan of 69 patients.

3.3.4. Mayo clinic dataset

This dataset is provided by non-profit organization named Mayo Foundation for Medical Education and Research for medical research purpose. This database contains numerous EHR's & Genetic test report of 07 cancer types. Total of 794(n = 794) cancer patient's instances are present in this, containing lung cancer (n = 223), colon/rectum cancer (n = 140), liver cancer (n = 107), prostate cancer (n = 66), pancreas cancer (n = 104), ovarian cancer (n = 91) and breast cancer (n = 53).

3.4. Pancreas cancer datasets

3.4.1. National centre for biotechnology information (NCBI)

NCBI provide genetic & biomedical information for advancement of science & healthcare. Its repository contains various Gene Expression array profile, clinical features, genomic sequence & protein database targeting multiple disease type, making it suitable choice for genomic research & experimental purpose.

3.4.2. Surveillance, epidemiology and end results (SEER)

SEER, an initiative by NCI, provides database having multiple features and statistics corresponding to multiple cancer type for research and analysis purpose. Mostly these datasets have been used for prognosis and prediction/forecasting of survival rate & spread of cancer disease purpose.

3.4.3. The cancer imaging archive (TCIA)

TCIA, public database, provides access to thousands of medical images of multiple modalities like CT, MRI, MG, MR, HS, US etc. for various type of common and rare cancer types for research purpose. Metadata available with each dataset makes it a reasonably good choice for experiment task. In regard to pancreas cancer, it holds multiple datasets having thousands of CT, MRI, pathology images from hundreds of pancreas cancer patients to use.

3.4.4. Medical segmentation decathlon (MSD)

MSD challenge database consist of 10 public datasets of 10 cancer type readily available for research and segmentation algorithm benchmarking purpose. Initially these datasets were provided for a biomedical image analysis competition in 2018, however dataset is still available to use for research purpose. There are 420 3D scans of pancreas cancer patients in CT modality with corresponding labels and pre-defined train & test set.

3.4.5. Gene expression omnibus (GEO)

GEO is a public genomic data repository containing various gene expression dataset for multiple diseases and data is open for research and social good purpose. There are various datasets i.e., GDS4899, GDS4935, GDS5323 & so on, present related to pancreas cancer having expression profiling for experimentation purpose.

3.5. Brain cancer datasets

3.5.1. Brain tumor segmentation (BraTS)

BraTS challenge is organized every year with the aim to evaluate state of the art segmentation & classification method used by researcher from all over the world. Every year they come up with updated dataset for brain tumor detection having thousands of multi-parametric magnetic resonance imaging (mpMRI) scans, from hundreds of patients, annotated by clinical experts. Most commonly used version are BraTS 2012, 2015, 2017 & 2019. Its latest version BraTS 2021 contains 8000 mpMRI scans from 2000 subjects publicly available to use.

3.5.2. Figshare

Figshare is another open-source repository of datasets of multiple diseases readily available for experimentation & research purpose. Figshare's brain tumor dataset conation 3064 T^1-weighted contrast enhanced MRI from 233 patients having three kind of brain tumor, meningioma (708 MRI), glioma (1426 MRI), and pituitary tumor (930

MRI), with respective labels for accurate classification purpose.

3.5.3. Cancer genome atlas glioblastoma multiforme (TCGA-GBM)

TCGA-GBM is a public dataset comprising of 481,518 images of CT, MRI & Digital Radiography (DX) modalities from 262 brain cancer patients provided by TCIA group for research & experiment purpose. This dataset also has provision to provide genomic data of thousands of genes responsible for brain cancer using GDC Data Portal.

3.5.4. TCIA-brain tumor progression dataset

This open-source dataset contains 8798 T^1 weighted MRI images of 20 subjects with tumor mask provided. This is also a part of TCIA public access group, which provide medical data of multiple modalities for research & experimental purpose for social good & innovation.

3.5.5. Ischemic stroke lesion segmentation (ISLES)

ISLES is a one of the image segmentation competitions in medical area aimed to supply medical data particularly for segmentation algorithm benchmarking purpose, it is organized almost every year and data is provided by Sicas Medical Images Repository (SMIR) under Open Database License. ISLES 2018 dataset contains 64 MRI from 63 subjects for research & evaluation of state-of-the-art ML techniques.

3.6. Skin cancer datasets

3.6.1. PH2

PH2 dataset is provided by Automatic Computer based diagnosis System for dermoscopic Images (ADDI) project for social good & development of efficient & automatic image analysis system using dermoscopic images. This dataset has 200 dermoscopic images of melanocytic skin lesions (80-common nevi, 80-atypical nevi & 40-melanomas).

3.6.2. International skin imaging collaboration (ISIC)

ISIC, an industry academic partnership designed to motivate use of digital skin images to reduce melanoma mortality, provide open-source data set every year since 2016 for education, research & experiment purpose. ISIC 2020 dataset contains 44118 dermoscopic images from 2746 patients having train set of 33136 images from 2056 subjects & test set of 10982 images from 690 subjects.

3.6.3. Cancer genome atlas skin cutaneous melanoma (TCGA-SKCM)

TCGA-SKCM is a cancer genomic initiative by NCI to elevate genomic research & education in skin cancer diagnosis. This dataset has multiple genomic records of thousands of genes and mutation data from 470 subjects of skin cutaneous melanoma.

3.6.4. Dermis & dermquest

Another most popular skin cancer dataset is DermIS & DermQuest. Former one contains 69 Dermoscopic images (43-melanoma & 36-normal cases) of skin cancer subjects and later on has 134 Dermoscopic images (76-melanoma & 58-normal cases).

3.6.5. IEEE international symposium on biomedical imaging (ISBI)

ISBI, a scientific conference organized every year for accelerate development of efficient algorithm for biomedical imaging, conduct many tumors type segmentation challenges & provide dataset for the same. Dataset is of varying sizes for every year, ISBI 2017 dataset contains more than 10000 dermoscopic Images from hundreds of skin cancer subjects available for experimentation purpose.

4. Literature selection methodology

Research approach carried out throughout this study is govern by commonly used method referred as SLR (Systematic Literature Review). At the beginning of research, research objective was decided, which was to identify the recent best machine learning methods applied in cancer diagnosis area by researchers during the year 2016–2021. As there are plentiful numbers of cancer types available for research in context of medical diagnosis, we narrow down our study for six cancer types i.e., liver, brain, lung, breast, skin & pancreas cancer.

After formulating our research problem for this review, next phase of this study was to find suitable papers related to stated problem, during which we started our literature search using different search keywords i.e., machine learning methods, cancer detection, CAD system, cancer diagnosis etc. In order to attain good literatures related to research subject, many renowned publisher's database, popular in scientific & research community, were utilized during searching i.e., IEEE Xplore, ScienceDirect, SpringerLink, Wiley, MDPI, PubMed, PMC and other medical journal publishers. Most of the proportion of selected papers (90%) for this study belongs to above mentioned publishers & rest of the proportion include some academic & disease specific medical journals i.e., Biomedical Research, arXiv, Taylor & Francis, Academia, ACM, EPRA etc (see Fig. 5).

After literature search completion, we used Inclusion-Exclusion based filtering method to select appropriate literatures for our study. Fig. 6 depicts different literature inclusion-exclusion criteria used in this study.

During paper search & selection procedure, we extracted more than 500+ articles for the study and started abstract based filtering on the basis of above-said inclusion-exclusion criteria along with year wise and cancer type wise clustering of selected papers. After going through abstract of paper we have selected top three articles for each year (from Year 2016 to Year 2021) related to individual cancer type chosen for review on the basis of highest accuracy observed or novelty of proposed method in the article. Hence as per above SLR we were able to select 18 most suitable article on each cancer type, making it total of 108 articles related to six cancer types selected for study. Next section describe cancer type wise literature survey of selected articles in brief along with extracted attributes-based tabulation of the same.

5. Literature survey

This section presents cancer type-wise comprehensive literature review of previous studies carried on application of ML/DL-based methods in cancer detection field for the period of six years between years 2016–2021.

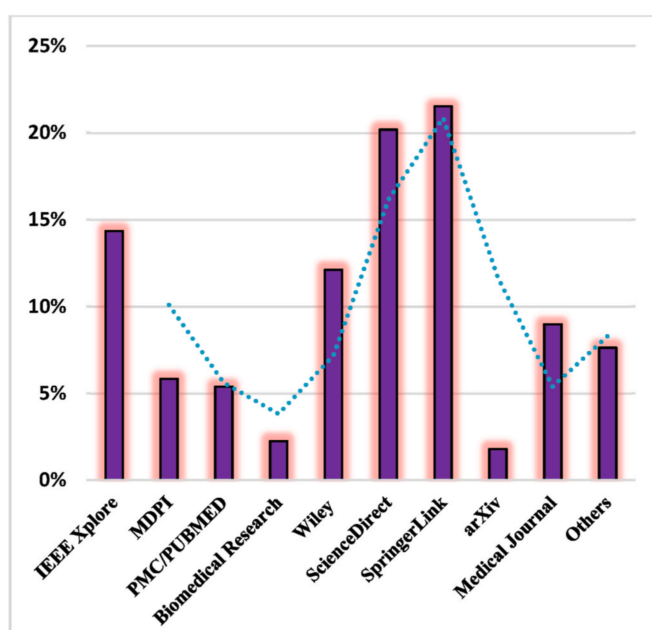

Fig. 5. Literature search databases & their share in this study.

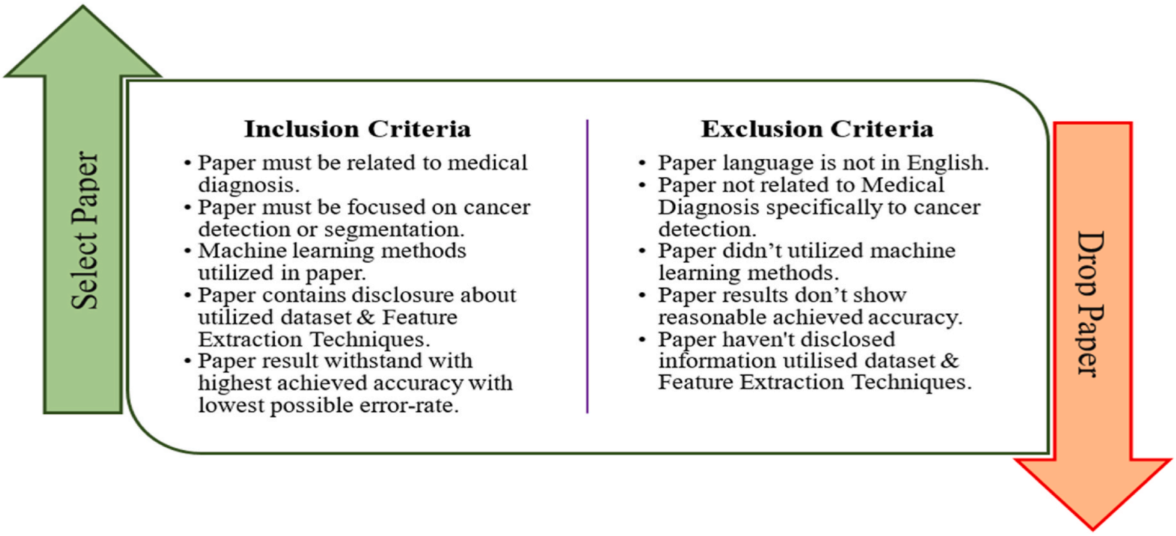

Fig. 6. Inclusion & exclusion criteria.

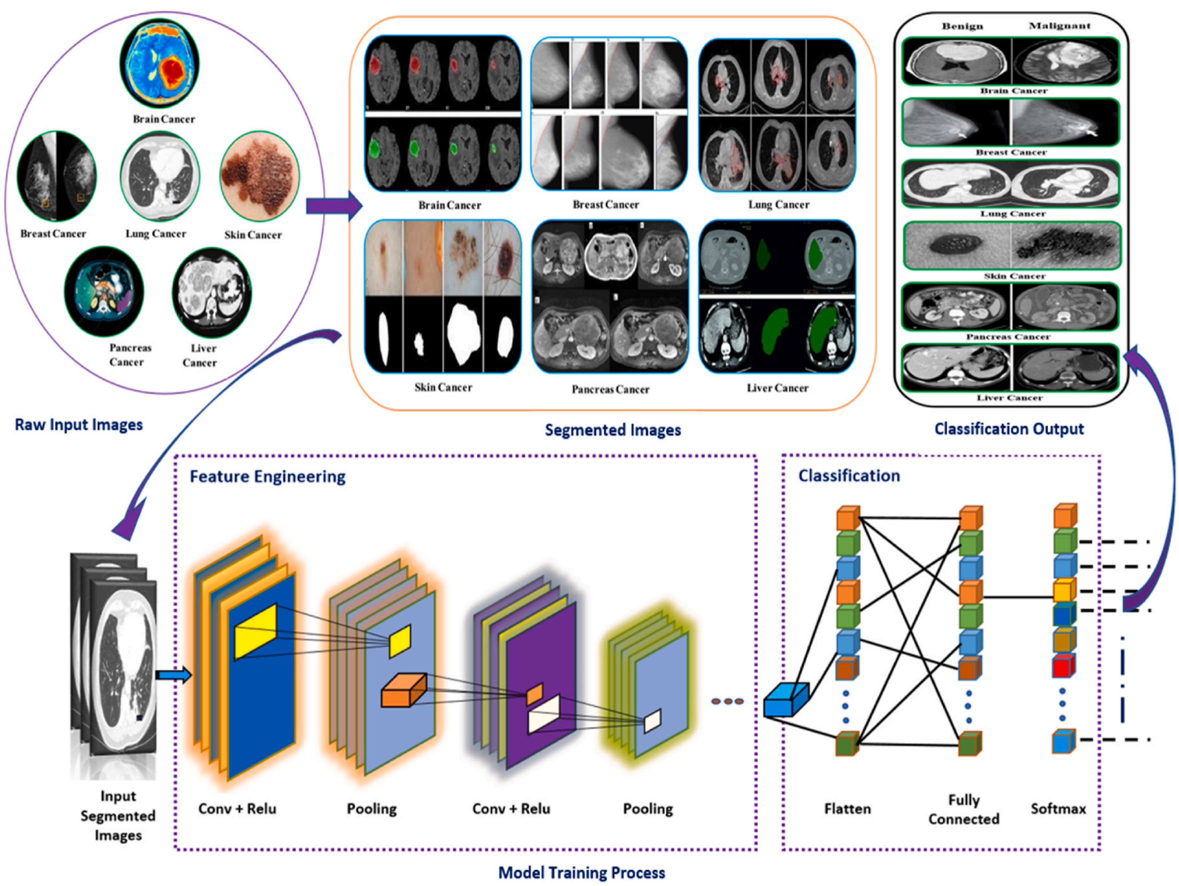

Fig. 7. Segmentation & classification process using deep learning technique.

5.1. Lung cancer

Lung cancer is one of the foremost cause of mortality among all mortalities world-wide due to any disease with an estimated mortality rate of 03% and contribution of 19% to overall moralities by all cancer types in year 2020 [1]. Patient's condition could be controllable in case of tiny sized tumor as those can be detached by some operational & surgical treatment at early stages only. However, unfortunately, due to a smaller number of visible symptoms at early stage, it is found to be very difficult to diagnose this disease in its early stages [43]. More than 70% of the symptoms are visible at later stages only. 5-year survival rate for lung cancer patients is about 18%, which could be increased to 55% if diagnosed at early stages [44].

There are several techniques with the help of which various diseases can be early diagnosed. Some of the popular & efficient techniques are machine learning and deep learning-based methods, which helps in diagnosing diseases in its early stage by processing medical data of different modalities like CT, PET, MRI, EUS & HS etc. Medical diagnosis using medical image processing primarily deals with segmentation and classification process using various DL-based methods. Fig. 7 presents segmentation & classification of various cancer types using most widely employed DL-based method, named CNN architecture [45]. Researchers working in the field of medical diagnosis performed many experiments on dissimilar medical dataset available publicly using multiple state of the art ML/DL algorithms, in search of most suitable segmentation & classification model for lung cancer detection, as presented in Table 1.

Fermino et al. [46], employed cascade support vector machine (C-SVM) classification algorithm on most common lung cancer dataset named LIDC-IDRI to detect and diagnose pulmonary nodules on CT images, clocking 97% accuracy using feature extraction (FE) techniques i.e., watershed transform (WT), histogram of oriented gradient (HOG) and principal component analysis (PCA) with internal validation. Setio AAA et al. [47], proposed a kind of novel CAD system using multi-view convolutional network (2D-ConvNet) on LIDC-IDRI dataset with data augmentation & regularization (dropout) techniques to reduce over-fitting problem in classification of solid, sub solid & large nodules. This novel method received 0.996 accuracy in terms of area under the receiver operating curve (AUROC) with external validation on ANODE09 (University Medical Center-Utrecht) & DLCST (Danish Lung Cancer Screening Trial) datasets. Wenquen et al. [48], evaluated three DL algorithm named CNN, deep belief networks (DBNs), stacked denoising auto encoder (SDAE) on LIDC dataset (1024 labelled CT images) and recorded accuracy of 79.76%, 81.19% & 79.29% respectively showing promising performance over designed traditional CAD system (SVM) with accuracy of 79.40%. To increase sample size, data augmentation was employed, resulting generation of 174412 samples.

Shen W et al. [49], proposed multi-crop CNN (MC-CNN) for automatic extraction and correct classification of suspicious malignant lung nodules with an accuracy of 87.14%. Wang H et al. [50], evaluated CNN algorithm against 04 classical ML algorithm on self-procured dataset of 168 patient's CT/PET images having 1397 lymph nodes collected from Harbin Medical University's Hospital, Harbin, China for classification of mediastinal lymph node metastasis of NSCLC and observed accuracy of 83.15% for SVM, 85.08% for Random Forest (RF), 85.35% for adaptive boosting (AdaBoost), 85.51% for back propagation artificial neural network (BP-ANN) and 85.64% for CNN. FE techniques used were gray-level co-occurrence matrix (GLCM), neighborhood gray-tone difference matrix (NGTDM) & gray-level zone size matrix (GLZSM). De Carvelho Filo et al. [51], achieved 93.19% classification accuracy using proposed ML-based methodology named SVM-radial base function (RBF) with Otsu threshold algorithm, minkowski functionals (MFs), distance measurements, skeleton-based measurements, triangulation-based measurements techniques as FE methods and genetic algorithm (GA) as feature selection (FS) method for detection of lung nodules out of 1405 nodules from 833 samples of LIDC-IRDC dataset.

Jiang H et al. [52], reported accuracy of 0.97 (AUROC) using multi group-patch based system called 4-Channel CNN, with Frangi filter, Otsu threshold algorithm as FE techniques after examining various bundles of nodule patches (25723 2D nodules), collected from 1006 CT images of LIDC-IRDC dataset. Naqi SM et al. [53], proposed a method of automatic detection and classification of the lung cancer to facilitate radiologists in diagnosing process using autoencoder & Softmax, clocking 96.9% classification accuracy on LIDC-IRDC dataset consisting of 777 nodules from selected 888 CT scans. Fractional-order darwinian particle swarm optimization for region extraction, gray tone Spatial dependence matrices (GTSDM) for texture feature and hybrid geometric texture feature descriptor for shape features were utilized as FE techniques. Coudray N et al. [54], trained a deep CNN (Inception V3) using 1634 whole slide HS images from TCGA-LUSC databases hitting accuracy of 0.97 (AUROC), which was found to be comparable to pathologist's performance.

Xie H et al. [55], proposed a novel automated pulmonary nodule detection model with 2D-CNN on 888 annotated CT scan of LUNA16 dataset hitting 86.42% accuracy. VGG16, deep neural model, with data

Table-1
Recent methods, dataset, feature extraction techniques, modality and result for lung cancer detection.

Reference	Methodology	Feature Extraction Techniques	Datasets	Modality	Results
Firmino et al. [46],	C-SVM	WT/HOG/PCA	LIDC-IDRI	CT	97% (Accuracy)
Setio AAA et al. [47],	2D-ConvNet	Automatic (Kernel/Filter)	LIDC-IDRI/ANODE09/ DLCST	CT	0.996 (AUROC)
Wenqing S et al. [48],	CNN/DBN/SDAE	Automatic (Kernel/Filter)	LIDC	CT	79.76%/81.19%/79.29% (Accuracy)
Shen W et al. [49],	MC-CNN	Automatic (Multi-crop pooling strategy)	LIDC-IDRI	CT	87.14% (Accuracy)
Wang H et al. [50],	SVM/RF/AdaBoost/BP-ANN/CNN	GLCM/NGTDM/GLZSM	Self-Procured	PET/CT	83.15%/85.08%/85.35%/80.51%/ 85.64% (Accuracy)
De Carvalho Filho et al. [51],	SVM-RBF	Otsu's/MFs/GA	LIDC-IDRI	CT	93.19% (Accuracy)
Jiang H et al. [52],	4-Channel CNN	Ostu/Automatic (Kernel/ Filter)	LIDC-IDRI	CT	0.97 (AUROC)
Naqi SM et al. [53],	Auto-Encoder	DPSO/GTSDM	LIDC-IDRI	CT	96.9% (Accuracy)
Coudray N et al. [54],	Inception V3(DCNN)	Automatic (Kernel/Filter)	TCGA	HS	0.97(AUROC)
Xie H et al. [55],	2-D CNN, Faster R–CNN	VGG16	LUNA16	CT	86.42% (Accuracy)
Naqi SM et al. [56],	SVM/KNN/NB/AdaBoost	HoG/PCA	LIDC	CT	98.6%/83.4%/93.3%/99.2% (Accuracy)
Khan SA et al. [57],	SVM	GLCM/LBP/DWT	LIDC	CT	98.35% (Accuracy)
Asuntha A and Srinivasan. [58],	FPSO–CNN	HoG/LBP/SIFT/FPSO	LIDC/Self Procured	CT	95.62 (Accuracy)
Shanthi S et al. [59],	DT/NB/NN	GLCM/SDS	TCGA	HS	87.41%/88.52%/89.63% (Accuracy)
Shakeel PM et al. [60],	Ensemble Classifier	GAWA/PSOMS/ACO/HSOGR/ VGG	TCIA	CT	97.61% (Accuracy)
SORI WJ Et al. [61],	DFD-Net(Two Path CNN)	DR-Net/Fusion/U-Net	KDSB-2017/LUNA 16	CT	96.66% (Accuracy)
Tian P et al. [62],	DCNN	KNN/DenseNet121/WT/ GLCM	PD-L1	CT	0.78 (AUROC)
Al-Obeidat F et al. [63],	Cascading classifier (CatBoost/ SVM, RF, MLP)	ABC/TMM	TCGA-LUSC	RNA	98.5% (Accuracy)

ANODE - Automatic nodule detection, DLCST - Danish lung cancer screening trial, R–CNN - Region-based convolutional neural network, VGG - Visual geometry group, SIFT - Scale invariant feature transform, DT - Decision tree, NN - Neural network, SDS - Stochastic diffusion search, GAWA - Genetic algorithm with wrapper approach, PSOMS - Particle swarm optimization-based multi-objective selection, ACO - Ant colony optimization, HSOGR - Hybrid swarm intelligent rough set, CatBoost - Category boosting, MLP - Multi-layer perceptron, ABC - Artificial bee colony segmentation, TMM - Trimmed mean of M-values, RNA - Ribonucleic acid.

augmentation & down sampling has been applied as feature extractor. Naqi SM et al. [56], evaluated ML classifiers named k-nearest neighbor (KNN), naive bayesian (NB), SVM and AdaBoost with HoG, PCA, optimal gray level threshold and first order histogram FE techniques on 1010 CT scans from LIDC dataset. Experiments performed, recognized AdaBoost as best classifier with a classification accuracy of 99.2%, surpassing KNN, NB & SVM performance. Khan SA et al. [57], proposed novel framework, comprising of multiple phases including image contrast enhancement, segmentation & classification phases and using SVM classifier with GLCM, local binary pattern (LBP), daubechies wavelet transform (DWT) feature extractor to classify nodule as benign & malignant from 836 candidate nodules from LIDC dataset receiving 98.35% classification accuracy.

Asuntha A and Srinivasan., [58], proposed novel DL-methods named fuzzy particle swarm optimization-CNN (FPSOCNN) by combining fuzzy particle swarm optimization (FPSO) algorithm as feature selector & CNN as classifier. Hog, LBP, SIFT and zernike moment feature descriptor were utilized for extracting texture, geometric, volumetric and intensity features of cancerous lung nodules on 1018 CT images from LIDC dataset and 1000 self-procured CT images from Arthi scan hospital, Tirunelveli, Tamilnadu. FPSOCNN model clocked average accuracy of 95.62% surpassing other traditional classifiers i.e., SVM, NB, KNN, AdaBoost, CNN etc. performance on same samples size. Shanthi S et al. [59], experimented on 270 HS scans from TCGA database using DT, NB & NN classifier with novel wrapper-based feature selection algorithm known as modified-SDS along with GLCM & Gabor filter FE methods. With a classification accuracy of 87.41%, 88.52% and 89.63% respectively, SDS based classifier outperformed correlation-based feature selection (CFS) & minimum redundancy maximum relevance (MRMR) based classifier.

Shakeel PM et al. [60], introduced new optimized ML technique for automatic lung cancer detection using improved deep neural network (IDNN)-VGG as segmenting technique & Ensemble classifier as classification technique. On experimenting over 5043 CT images of TCIA dataset with proposed & other traditional classifier i.e. NB, RF, instance based learner (IBK), J48 (decision tree) etc., accompanied by GAWA, PSOMS, ACO & HSOGR feature selection techniques, author identified proposed model more efficient than others used classifier with a received accuracy of 97.61%.

Sori WJ et al. [61], introduced novel DL-based method named "denoising first two-path CNN" (DFD-Net), consisting of denoising & detection phase to detect lung cancer nodule from total of 2989 CT scans (2101 from KDSB and 888 from LUNA 16 challenge dataset) clocking 96.66% accuracy. Residual learning denoising model (DR-Net) was utilized in denoising phase & two path CNN in later phase with FE techniques i.e., discriminant correlation analysis, thresholding methods, gaussian filter & segmentation method U-Net. Tian P et al. [62], trained & optimized a DCNN on 939 CT scans of consecutive stage IIIB-IV NSCLC patients from PD-L1 dataset & obtained accuracy of 0.78 (AUROC). Along with DCNN, KNN, DenseNet121, Mann Whitney *U* test, WT & GLCM were utilized as FE methods.

Al-Obeidat F et al. [63], proposed two-stage cascading classifier with CatBoost classifier at former stage & SVM, RF & MLP classifiers at later one for lung cancer detection using oncogenomic (RNA & Gene expression) sequence containing 23396 features from 550 RNA sequence samples from TCGA-LUSC dataset. Accuracy of 98.5% had been recorded by employing TMM for normalization, discrete filtering with binary artificial bee colony method-ABC and synthetic minority oversampling technique as FE methods.

5.2. Breast cancer

With an estimated morality rate of 01% world-wide out of all death by all diseases and having contribution of 07% mortality in all mortalities due to all cancer types world-wide, breast cancer has been recognized as fourth-most cause of mortality around the world in year 2020, specifically prevalent to women [1]. Breast cancer typically happens due to abnormal or irregular growth of cells in breast. With higher rapid division than regular cell, these cells start accumulating and forming lump or mass into the breast making it too dangerous for patient [64,65]. MG, thermographic (TG), US, CT, MRI scans, EHR and genomic sequences are most common employed modalities in breast cancer diagnosis [9,66]. Several researchers developed & experimented various ML/DL algorithm on WBCD, MIAS, DDSM, TCGA-BRCA & some other private datasets for early detection of Breast cancer, identifying ML techniques efficient enough to segment & classify breast cancer correctly, as presented in Table 2 [6,67,68].

Abdel-Zaher et al. [69] developed novel DBN-based CAD system having unsupervised training phase backed by a supervised back propagation (BP) neural network phase (DBN-NN) along with liebenberg marquardt learning function to classify breast cancer nodule from 690 mammographic images collected from WBCD dataset publicly available for research & experiment purpose. Furthermore, on comparing with RIW-BPNN performance on the same dataset, DBN-NN outperformed RIW-BPNN model with an accuracy of 99.68%. Vural, S et al. [70], demonstrated the efficient use of gene mutation profiles along with unsupervised ML algorithms to foster a classification model to predict breast cancer from exome sequence of 358 homogenous patients from TCGA-BRCA dataset. Ranking & scoring of gene impacts was done by combined annotation dependent depletion (CADD) method, followed by clustering of 358 patients into 03 distinct subgroups was performed by using non-negative matrix factorisation (NMF) method. Five ML algorithms, RF, SVM, J48/C4.5 (DT), NB & KNN, was employed with 10-fold cross validation (CV) over collected exome sequence data to identify clinically divergent breast cancer using somatic gene mutation and observed RF as the best classifier among above said classifiers with a reasonably fair accuracy of 70.86%.

Kanchanamani M and Varalakshmi P., [71], investigated non-subsampled shearlet transform (NSST), image resolution decomposition method, along with five ML algorithm named SVM, NB, KNN, MLP and Linear discriminant analysis (LDA) on 322 MG images of MIAS dataset for the diagnosis of breast cancer. Shearlet transform, GLCM & images cropping methods were being used as FE techniques. Investigation result identified SVM with NSST as best classifier with an accuracy of 92.5%. Sun W et al. [72], developed graph-based semi-supervised learning model using DCNN containing four module named feature-selection, data-weighing, dividing co-training procedure based confident labelling and CNN for diagnosing breast cancer using 1874 full-field digital mammogram (FFDM) images procured from University of Texas, United States. Model was developed on considering the need of small number of labelled data for model training purpose. Proposed model clocked fair accuracy of 82.43% on small mixed labelled data against accuracy of 85.52% on fully unlabelled data. GLCM, PCA, LDA, multidimensional scaling (MDA), data augmentation & exponential function was used for FE during experiment. Mughal B et al. [73], presented a BPNN-based classification model for automating the diagnosis of the breast tumor by reducing false positive rate during classification process. The proposed model was evaluated on total 1187 mammographic images (437-MIAS dataset & 750-DDSM dataset) along with Top-Hat transformation, GLCM and cropping methods as FE. With the observed reduction in false positives rate, proposed method achieved improved accuracy of 97% (DDSM) & 98% (MIAS).

Singh BK et al. [65] introduced a novel CAD system for classification of breast lesions by integrating BPANN, SVM and radiologist feedback with the aim of improving clinical efficiency of US modality-based CAD systems. Experiments was performed on a self-procured database of 178 ultrasound images of breast anomalies collected from Pt. J. N. M. Government Medical College and Baba Saheb Ambedkar Hospital Raipur (Chhattisgarh) along with FE techniques named despeckle filter-based wavelet decomposition, majority voting & rank aggregation method, cropping & scaling. With an improved accuracy of 98.62% over standalone BPANN & SVM based model's performance, proposed model found better to diagnose breast cancer using US images. Amrane M et al.

Table 2
Recent methods, dataset, feature extraction techniques modality and result for breast cancer detection.

Reference	Methodology	Feature Extraction Techniques	Datasets	Modality	Results
Abdel-Zaher et al. [69],	DBN	Liebenberg Marquardt/NN	WBCD	MG	99.68% (Accuracy)
Vural, S et al. [70],	RF/SVM/J48-C4.5/NB/KNN	CADD/NMF	TCGA-BRCA	Genomic	70.86%/69.16%/60.11%/57.24%/49.17% (Accuracy)
Kanchanamani M and Varalakshmi P. [71],	SVM/NB/MLP/KNN/LDA	NSST/GLCM/Cropping	MIAS	MG	92.5%/58.3%/48.3%/55.0%/59.1% (Accuracy)
Sun W et al. [72],	DCNN	GLCM/PCA/LDA/MDS/Data Augmentation/Exponential Function	Self-Procured	MG	82.43% (Accuracy)
Mughal B et al. [73],	BP-NN	Top-Hat transformation/GLCM/Cropping	DDSM/MIAS	MG	97%/98% (Accuracy)
Singh BK et al. [65],	BPANN/SVM/BPANN + SVM + Expert Opinion	DWT/Cropping/Scaling/Majority Voting/Rank Aggregation	Self-Procured	US	90%/88.28%/98.62% (Accuracy)
Amrane M et al. [74],	KNN/NB	Data Wrangling/Data Scaling,	WBCD	EHR	97.51%/96.19% (Accuracy)
Sadad T et al. [75],	DT/KNN	FCMRG/LBP-GLCM/LPQ/mRMR/Cropping	MIAS/DDSM	MG	98.2%/94.4% (Accuracy)
Banu AB et al. [76],	BBN/BAN/TAN	GB/Data Wrangling & Scaling	WBCD	EHR	91.70%/91.70%/94.11% (Accuracy)
Vijayarajeswari R et al. [77],	SVM/LDA	Hough Transform/Canny Edge Detection/Maximization Estimation	MIAS	MG	94%/86% (Accuracy)
Dhahri H et al. [78],	GB/DT/RF/KNN/AdaBoost/SVM/ET	GP/Standard Scaler/PCA	WBCD	EHR	95.57%/93.8%/96.45%/91.11%/98.23%/51.1%/97.34% (Accuracy)
Bayrak EA et al. [79],	SMO/LibSVM/MLP/Voted Perceptron	Data Wrangling & Scaling	WBCD	EHR	96.99%/95.79%/95.44%/90.98% (Accuracy)
Zhou LQ et al. [80],	Inception V3/Inception-ResNet V2/ResNet-101	Data Augmentation/Automatic (Filter/Karnal)/Adam	Self-Procured	US	80%/82%/78% (Accuracy)
Acharya S et al. [81],	ELF (SVM)	ResNet50/CNN/PCA/KNN/Fusion	Self-Procured	HS	97.05% (Accuracy)
Muhammet Fatih Ak. [82],	LR/KNN/SVM/NB/DT/RF/RoF	Data Scaling/Correlation Metrics	WBCD	EHR	98.06%/96.49%/96.49%/94.73%/95.61%/95.61%/97.40% (Accuracy)
Jiande W et al. [83],	KNN/NB/DT/SVM	FDR/Log2 FC	TCGA	RNA Sequence	87%/85%/87%/90% (Accuracy)
Karthiga R et al. [84],	Cubic SVM/Quadratic SVM/Linear SVM	Top-Hat & Bottom-Hat Transforms/GLCM/Curvelet Transform & Wrapping	Visual laboratory Database	TG	93.30%/90%/88.30% (Accuracy)
Lahoura, V et al. [85],	ELM (ANN)/AdaBoost/KNN/NB/Perceptron/SVM	Gain Ratio/ELM/Data Scaling	WBCD	EHR	96.92%/92.98%/90.64%/84.80%/83.04%/92.98% (Accuracy)

MDS - Multidimensional scaling, FCMRG - Fuzzy C-means and region-growing based technique, LPQ - Local phase quantization, BBN - Bayes belief network, BAN - Boosted augmented naive bayes, TAN - Tree Augmented Naive Bayes, GB - Gradient Boosting, ET - Extra Tree, GP - Genetic Programming, SMO - Sequential minimal optimization, LibSVM - Liblinear SVM, Adam - Adaptive Moment Estimation, ELF - Enhanced Loss Function, LR - Logistic regression, RoF - Rotation Forest, FDR - False discovery rate, Log2 FC - Log2 Fold change, ELM - Extreme learning machine.

[74], applied NB & KNN classifier on 683 EHR samples of breast cancer patient from WBCD dataset to find efficient model to detect breast cancer. By applying data wrangling & scaling methods in pre-processing part of classification, authors were able to receive accuracy of 97.51% (KNN) with lowest error rate then NB classifier with an accuracy of 96.19% during classification.

Sadad T et al. [75], proposed CAD system for breast cancer classification task by evaluating DT, KNN, SVM, LR, LDA & ensemble classifier on 109 images of MIAS and 72 images of DDSM databases. FCMRG, LBP-GLCM, LPQ and mRMR algorithms were utilized for segmentation purpose as FE methods. With an observed accuracy of 98.2% on MIAS dataset and 95.8% on DDSM dataset, DT using hybrid features (LBP-GLSM + LPQ) & KNN using LPQ features outperformed other used classifier in the study. Banu AB et al. [76], compared three ML classifiers named BBN, TAN & BAN for analysing 669 EHR instances having 32 attributes from WBCD database to find best performing classifier among above three classifiers. GB, data wrangling, data scaling techniques were utilized as FE methods during experiment and TAN was identified as best classifier with an accuracy of 94.11% in breast cancer classification task.

Vijayarajeswari R et al. [77], implemented SVM & LDA classifiers with FE techniques like hough transform-shape, canny edge detection -edge & maximization estimation method-segmentation on 92 out of collected 322 MG images of breast cancer patients from MIAS dataset. Furthermore, with an achieved accuracy of 94%, SVM classifier outperformed LDA classifier with a significant margin of 08%. Dhahri H et al. [78], suggested ML-based approach in combination of GP to distinguish between benign & malignant breast tumor using EHR of 569 patients collected from WBCD dataset. On experimenting with GB, DT, RF, KNN, Adaboost, SVM, & ET classifiers along with FE methods i.e., GP, data scaling & PCA on dataset, Adaboost classifier performed best with a fair accuracy of 98.23% making it suitable for early breast tumor detection in controlled parametric setting.

Bayrak EA et al. [79], compared two SVM-based and two ANN-based classifiers named SMO, LibSVM, MLP & Voted Perceptron over 669 EHR instances consisting of 11 integer attributes of breast cancer patients collected from WBCD dataset with 10-fold CV. SMO classifier was found best performing classifier among all employed classifiers with an accuracy of 96.99%. Zhou LQ et al. [80], proposed a DL-based model to efficiently identify breast cancer from US scans of primary breast cancer patients. Three variants of CNN called Inception V3, Inception-ResNet V2 and ResNet-101 architectures with data augmentation & Adam optimizer had been employed to find best CNN architecture for breast cancer detection. Models were trained on dataset of 974 US images of 756 patients procured from Tongji Hospital, Wuhan, China & validated on dataset of 81 US images of 81 patients collected from Hubei Cancer Hospital, China. With the accuracy of 82%, Inception-ResNet V2 based model was observed to be more efficient than rest two model in breast cancer classification task.

Acharya S et al. [81], introduced a novel CAD system to automate and enhance processing time & accuracy of breast cancer classification method with ELF, a blend of SVM loss function & optimization problem, having pre-processing, patch extraction, FE, clustering & classification stages. Proposed model was evaluated on dataset of 22000 HS images of 1427 women collected from department of radiology, University of Pittsburgh School of Medicine, USA and received accuracy of 97.05%. FE techniques utilized were linear transformation, ResNet50 & CNN, PCA, KNN and fusion. Muhammet Fatih Ak., [82], investigated multiple ML classifier like LoR, KNN, SVM, NB, DT, RF & RoF along with data normalization, scaling & correlation metrics over 669 samples having 32 features in EHR modality collected from WBCD dataset. On comparative analysis of all utilized techniques, LR was identified as best classifier among all utilized, with an accuracy of 98.06%.

Jiande W et al. [83], proposed a ML approach for classifying triple-negative breast cancer patients by using gene expression data. KNN, SVM, NB & DT classifier were being evaluated on 1102 BCE RNA sequence samples from TCGA repository publicly available for social good. FDR & Log2FC were employed as FE technique during experimentation and result analysis suggest SVM as efficient classifier among other used with an accuracy of 90%. Karthiga R et al. [84], proposed SVM-based automatic breast cancer diagnosis system using thermographic images of breast cancer patients. Three variants of SVM i.e., cubic-SVM, quadratic-SVM & linear-SVM were investigated on extracted 60 numbers of front view thermal images obtained from publicly available dataset named visual laboratory, the Fluminense Federal University in Rio de Janeiro, Brazil and observed results found Cubic-SVM classifier as promising classifier among rest of used with an accuracy of 93.30%. Top-hat & bottom-hat transforms, GLCM, curvelet transform & wrapping methods were utilized as FE techniques during experimentation process.

Lahoura V et al. [85], introduced a novel CAD system for breast cancer detection using an ANN variant named ELM. Multiple other ML classifier i.e. AdaBoost, KNN, NB, MLP & SVM were also evaluated on 569 EHR instances of breast cancer patients from WBCD in two different computing space (standalone & cloud computing environment-Amazon EC2). Gain ration, ANN & data scaling techniques were employed as FE during evaluation phase and ELM classifier outperformed other used classifier with accuracy of 96.92% & 98.68% in standalone & cloud computing environment respectively.

Apart from breast cancer, cervical cancer is found to be leading cause of mortality among women around the world. This genital cancer typically occurs in cells of cervix, which is lower region of uterus that connects to the vagina. Infection received via sexual transmission of human papillomavirus (HPV) found to be key cause of cervical cancer among women. This cancer type is also hard to diagnose early as like many other cancer types as it doesn't display any symptoms in its early stage. Pelvic pain, vaginal bleeding & pain during intercourse and heavy bloody & watery discharge are the symptoms of advanced cervical cancer. This cancer has two main types named squamous cell carcinoma and adenocarcinoma, where former one is most frequent one & typically occurs in thin and flat cells forming outer layer of cervix and later one happens in glandular cells of cervix. Pap smear test is most commonly adopted test for detection & treatment of cervical cancer [86,87]. Although in the past this Pap smear test protected millions of lives world-wide, however it's been found time consuming job to perfectly analyse pep test. Advent of ML/DL-based methods introduced significant advancement in healthcare industry by adding new diagnosis line in parallel to traditional diagnosis methods in terms of improved efficiency & speed of diagnosis [42,88].

Various studies have done on cervical cancer detection using image processing-based methods so far, most of them observed to be struggling for accuracy due low quality of test images, moreover Pap smear test-based detection methods are susceptible to rotation and gray-scale variations in test images. In line with these challenges, Fekri-Ershad, S [87]. proposed an efficient method for cervical cancer detection using dataset of 917 Pap smear samples collected from Herlev University Hospital. By extracting statistical and textural information of the cytoplasm and nucleus and utilizing harlick features, global-significant-value & time-series features at feature extraction phase, author introduced accurate, less computationally complex & rotation invariant diagnosis method. Proposed method utilized KNN, bayesian network, J48 Tree and multi-layer perception as classifier and achieved better accuracy than other evaluated state-of-art classifiers.

Park, Y.R. et al. [89], developed a ML-based approach to classify cervical cancer using 4119 cervicography images. Basic cropping, GLCM, gray level run length matrix (GLRLM), gray-level size zone matrix (GLSZM), and laplacian of gaussian (LoG) were used as feature extractor and XGBoost, SVM, RF & CNN-based ResNet50 models were utilized as classifier during study. ResNet50 outperforms rest of used models with an accuracy of 0.97(AUC) during cervical cancer detection task.

Tanimu, J.J. et al. [90], proposed ML-based model for classification of cervical cancer using decision tree (DT) as classifier. Publicly available Risk Factors dataset from UCI has been considered for the study. least-absolute shrinkage and selection operator (LASSO), recursive feature elimination (RFE) & SMOTETomek oversampling method were utilized in pre-processing stage and led to improved accuracy of 98.72% of proposed model during cervical cancer classification process.

Singh, J. and Sharma, S [91]. proposed a ML-based model for cervical cancer stage prediction by evaluating Six machine learning algorithms named naïve-bayes, functions-based-logistic-SMO, lazy-based-LWL, meta-based-iterative-classifier-optimizer, rule-based decision-table, and trees-based-decision stump, on collected clinical sessor-based data of patients, which were validated for standard contextual information with data repository. Experimentation was done on eight different stage of cervical cancer using mentioned classifier and results identified decision tree-based classifier superior than others with a prediction accuracy of 77.97% along with tagging of stage-2b as most frequently predicted stage of cervical cancer.

Weegar, R. and Sundström, K [92]. proposed a machine learning based methodology for classification of cervical cancer using electronic health records (EHRs) of 1723 patients, collected from Karolinska University Hospital, Stockholm. These EHRs were supplemented with free text notes, lab results & clinical code for improving in prediction accuracy. Proposed model utilized four classifiers named SVM, RF, bernoulli NB & complement NB for prediction purpose along with RFE and ranking based feature selection method during experimentation. Obtained results identified RF classifier as best among other evaluated classifier with an accuracy of 0.97 (AUC) during classification of cervical cancer patients.

5.3. Liver cancer

On contributing estimated morality rate of 01% world-wide in all deaths by all diseases and having contribution of 06% mortality in all mortalities due to all cancer types world-wide, liver cancer has been recognized as fifth-most cause of mortality around the world in year 2020 [1]. Liver cancer generally formed due to development of mutation in liver cell's DNA, leading cell's uncontrolled growth to form mass of cancerous cells. Hepatocellular carcinoma is most common type of liver cancer among other types such as hepatoblastoma, cholangiocarcinoma and intrahepatic. It is more prevalent in male patients than female patients and most patients don't have symptoms in its early stages, hence ML techniques could be a possible solution for the same [93,94]. Several researchers developed various ML & DL algorithm on 3D-IRCADB-01, ILPD, LITS, Mayo clinic dataset & some other private datasets for early detection of liver cancer identifying ML techniques efficient enough to segment & classify breast cancer correctly. CT, MRI, US, PET, EHR and genomic sequences are commonly employed modalities in liver cancer diagnosis, as shown in Table 3 [10,95].

Ben-Cohen A et al. [96], proposed a fully convolutional network (FCN) based DL model for liver segmentation and liver metastases detection task using 80 CT images of 20 patients collected from Sheba medical center, Hashomer-Israel & SLIVER07 challenge dataset. Using small dataset, performance of FCN was compared with sparsity-based classification schemes along with patch-based CNN. With the accuracy of 0.86 & 0.6 in terms of true positive rate (TPR) & false positive rate (FPR) respectively proposed method was found superior than other used ones. Experiments performed was supplemented with data augmentation, 3-fold CV & automatic filter-based FE technique. Hsiao-Hsien R et al. [97], developed liver cancer prediction model using artificial

Table 3
Recent methods, dataset, feature extraction techniques, modality and result for liver cancer detection.

Reference	Methodology	Feature Extraction Techniques	Datasets	Modality	Results
Ben-Cohen A et al. [96],	FCN	Data Augmentation/Automatic (Filter/Kernel)	Self-Procured/ SLIVER07 Challenge	CT	0.86 (TPR)
Hsiao-Hsien R et al. [97],	ANN/LR	Chi-Square Test	NHIRD Dataset	EHR	0.837/0.778 (AUROC)
Luca S et al. [98],	Levenberg-Marquardt - BPN	Haralick Feature/Fourier Transform/Gabor Filter/DCT/Morphology	Self-Procured	US	97.58% (Accuracy)
Ilias G et al. [99],	SVM	RGB-to-Stiffness Inverse Mapping/Clustering/SR	Self-Procured	US	87.30% (Accuracy)
Moloud A et al. [100],	Boosted C5.0/ CHAID	Chi-Square Test/Boosting	ILPD(UCI)	EHR	93.75%/65% (Accuracy)
Chang CC et al. [101],	LR	GLCM/Elliptic Model/Fuzzy C-Means Clustering/Region Growing Algorithm/Backward Elimination Method	Self-Procured	CT	81.69% (Accuracy)
Xu Y et al. [102],	BoVW with SCM	Random Walk-Based Interactive Algorithm/Histogram Intersection/ LBP/PCA	Self-Procured	CT	80% (Accuracy)
Kim S et al. [103],	NN	Select-Eliminate method/ANOVA Test	Self-Procured	RNA Sequence	93.50% (Accuracy)
Frid-Adar M et al. [104],	CNN	GAN/Automatic (Filter/kernel)/Batch-normalization	Self-Procured	CT	85.7% (Sensitivity)/ 92.4% (Specificity)
Hamm CA et al. [105],	CNN	Data Augmentation/Automatic (Filter/kernel)/Cropping	Self-Procured	MRI	92% (Accuracy)
Romero FP et al. [106],	DNN	Inception-V3 & InceptionResNet V2/ImageNet/Back- Propagation/ Cropping/Mean Centring & Standard Deviation/Data Augmentation/ ADAM optimizer	LITS & Self Procured	CT	96% (Accuracy)
Książek W et al. [95],	SVM	GA with CV/Scaling/Imputation method	Self-Procured	EHR	88.49% (Accuracy)/ 0.8762 (F1-score)
Naeem S et al. [94],	MLP/SVM/RF/J48	Data Fusion/Gabor filters/Otsu's thresholding/Probability of Error & Average Correlation	Self-Procured	CT/MRI	99%/98.5%/98.17%/ 97.11% (Accuracy)
Almotairi S et al. [107],	SegNet	Replication/File Conversion/CNN/Data Augmentation/Automatic (Filter/kernel)	3D-IRCADB	CT	98.8% (Accuracy)
Devi RM et al. [108],	SVM	Region Growing Algorithm/Kernelized Fuzzy C-means Algorithm/ Morphological Operations/Cropping	3D-IRCADB & Self-Procured	CT	98.6% (Accuracy)
Ayalew YA et al. [109],	Modified U-Net	Scaling/Data Augmentation/Automatic (Filter/kernel)/Adam/Cross-entropy Loss Function	3D-IRCADB & LITS	CT	0.9612 (DSC)
Randhawa S et al. [110],	Enhanced SVM	Regularization function/Region Growing Algorithm/Weiner Filter/ GLCM/Watershed Method/	LITS	MRI	98.8% (Accuracy)
Oniani D et al. [111],	GNN	Frequency Threshold/Mayo's NLP & UMLS services/Multi-Hot Encoding/Scaling	Mayo Clinic Dataset	EHR	90.1% (Accuracy)

SLIVER - Segmentation of the liver, DCT - Discrete Cosine Transform, C5.0/J48 - Modified Decision Tree, CHAID - Chi-squared automatic interaction detection, BoVW - Bag of visual words, SCM - Spatial cone matching, ANOVA - Analysis of variance, GAN - Generative adversarial networks, Inception V3, ResNet, ImageNet, U-Net, SegNet - Modified CNN, DSC - Dice similarity coefficient, GNN - Graph neural network, NLP - Natural language processing, UMLS - Unified medical language system.

neural network (ANN) and LR for type II diabetes patients with in diagnosis span of 06 years. Dataset of 2060 EHR instances were collected from National Health Insurance Research Database (NHIRD)-Taiwan. Chi-square test was utilized for feature significance & selection purpose during the experimentation process and with the classification accuracy of 0.837 (AUROC), ANN-based model found to be superior to LR & other traditional ML algorithms during classification of liver cancer.

Luca S et al. [98], proposed levenberg-marquardt back propagation network (BPN) based classification system for automatic detection of fatty liver disease (FLD) using 124 US scans of 63 patients, self-procured from multiple institutions. Haralick, Fourier & discrete cosine transform, Gupta transforms and Gabor transform were utilized as FE techniques. Using random partitioning approach for classifier performance evaluation, proposed system achieved accuracy of 97.58% along with realized sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) of 98.08%, 97.22%, 96.23%, and 98.59% respectively. Ilias G et al. [99], introduced a CAD system for detection of chronic liver disease (CLD) using US-based shear wave elastography (SWE) imaging with SVM and stiffness value clustering method. FE techniques i.e., RGB-to-Stiffness inverse mapping, clustering, stepwise regression (SR), were employed on private dataset of 26 SWE US images of 126 individuals procured from School of Medicine, University of Patras, Rion and recorded accuracy of 87.30% surpassing performance of past clinical studies & domain experts in discrimination between healthy person & CLD patients.

Moloud A et al. [100], introduced novel DT-based prediction model for detection of liver disease by experimenting on two algorithms named CHAID and C.50. Experiment was performed on public dataset of 583 EHR instances collected from ILPD database. By applying Chi-Square Test & Boosting techniques as FE methods, defined model achieved accuracy of 93.75% for C.5.0 identifying boosted-C5.0 superior then CHAID-based model. Chang CC et al. [101], proposed a logistic regression-based CAD system for detecting liver tumor using multiphase CT images. Dataset used in the experiment contained 71 CT images of 59 subjects procured from Department of Medical Imaging, National Taiwan University Hospital, Taipei-Taiwan. GLCM, elliptic model, fuzzy c-means clustering, region growing algorithm & backward elimination were utilized as FE techniques during the experiment and LR along with leave one out CV, proposed model detected the accuracy of 81.69%.

Xu Y et al. [102], developed content-based images retrieval (CIBR) system using texture-specific BoVW method backed by SCM strategy for optimized focal liver lesions (FLLs) representation to ease radiologist's task in clinical diagnosis of liver cancer. Accuracy of 80% was achieved by developed model on applying FE techniques i.e., random walk-based interactive algorithm, histogram intersection, LBP, PCA, SCM etc., over self-generated database containing multiphase CT images from 132 patients comprising of five lesion type named focal nodular hyperplasia (FNH), cysts, HCC, metastasis (METS) and hemangiomas (HEM). Kim S et al. [103], proposed a NN-based hybrid feature selection method-based liver cancer detection using microarray (RNA Sequence). Proposed model was supplemented with 10-fold CV, select-eliminate (SE) Algorithm & ANOVA method for increasing performance of NN. After experimenting on self-procured dataset of 751 aptamers spot scans from 390 subjects, selected based on p-value, accuracy of 93.5% was achieved by proposed model during liver cancer diagnosis process.

Frid-Adar M et al. [104], presented a novel GAN-based DL approach for classification of liver lesions using patient's images of CT modality. CNN was used as classifier and GAN was utilized for synthesizing high quality liver lesion ROIs during the model development phase. The proposed model was evaluated on 182 CT scans of liver patients from Sheba Medical Center, Hashomer-Israel, containing three lesion types named cysts, metastases & hemangiomas. CNN along with GAN & batch normalization, clocked sensitivity of 85.7% & specificity of 92.4% during classification process and found GAN as a suitable option for resolving small dataset-size problem. Hamm CA et al. [105], developed a CNN-based DL-model for classification of common hepatic lesions using multi-phasic MRIs. CNN along with FE techniques i.e., data augmentation, ADAM optimizer & cropping, was evaluated on 334 MRI images having 490 lesions, which were collected from picture archiving and communication system (PACS) database. Accuracy of 92% was achieved by proposed model during classification process.

Romero FP et al. [106], proposed an end-to-end DNN-based discriminative system for classification of liver lesion. Inception-V3 & ResNet-V2, ImageNet, BP, ADAM optimizer were employed with DNN as FE during experiments. Dataset used in the study contained 230 CT images having 230 lesions of 63 patients, collected from both LITS challenge dataset & University of Montreal Hospital Centre, Montreal-Canada. With the accuracy of 96% & AUROC of 0.97 proposed system was found superior than other state-of-art ML methods. Książek W et al. [95], proposed a novel ML-based approach to detect HCC by integrating SVM classifier with GA. FE methods named GA, CV, scaling & imputation were applied on self-procured dataset having EHR instances of 165 patients having 49 features, collected from Coimbra's Hospital and Universitary Centre (CHUC), Portugal. After that classification was performed with SVM & other traditional classifiers like KNN, NB, LDA, and MLP. Experiment result showed superiority of SVM over other used methods in terms of classification performance with received f1-score of 0.8762 & accuracy of 88.49%.

Naeem S et al. [94], proposed a hybrid feature-based classification system using fused images, generated through fusion of CT & MRI scans of liver cancer subjects, for improving classification performance of ML techniques used during the classification process. Four ML classifiers i.e., MLP, SVM, RF & J48, along with FE techniques i.e., fusion, gabor filters, Otsu thresholding, probability of error & average correlation, were examined on private dataset of 1400 CT/MRI scans, collected from Bahawal Victoria Hospital, Bahawalpur, Pakistan. With an improved accuracy of 99%, MLP found to be better than SVM, RF & J48 classifier during the classification of benign & malignant liver cancer. Almotairi S et al. [107], proposed DL system using modified deep convolutional encoder-decoder architecture called SegNet, for semantic pixel-wise classification & segmentation of liver tumor using CT images to diagnose liver cancer. Dataset, experimented on, contained 3D scans of 20 patients in CT modality collected from public dataset 3D-IRCADB01. Using different method of FE & format conversion like replication, file format conversion, data augmentation & CNN, proposed system acquired the classification accuracy 98.8%, which seemed to be fair enough to enhance radiologist's performance during diagnosis process.

Devi RM et al. [108], proposed novel three-stage CAD system by making use of feature-difference method and SVM classifier for automatic segmentation & classification of liver tumor. Feature extraction was done using region growing algorithm, kernelized fuzzy c-means algorithm, morphological operations & cropping method. Dataset used contained 3D-CT scans of 20 patients from public dataset named 3D-IRCADB and 100 CT scans procured collectively from Aarthi Hospital, Velachery-Tamilnadu & KGS scan centre, Madurai-Tamilnadu. On experimenting on used dataset classification accuracy of 98.6% was achieved by proposed CAD system. Ayalew YA et al. [109], proposed a modified U-Net based DL method to segment liver tumor from abdominal CT scans of liver patients by modifying no of network layers & filters in baseline U-Net architecture to improve segmentation performance via reducing network complexity. Dataset used incorporates total of 2738 CT scans of 151 patients retrieved from two public datasets 3D-IRCADB & LITS. Using feature extraction techniques i.e., scaling, data augmentation, CNN, Adam optimizer & cross-entropy loss function, data augmentation-based U-Net outperformed baseline U-Net & U-net without augmentation model with an improved accuracy of 0.9612 in terms of dice score KPI.

Randhawa S et al. [110] proposed a hybrid model by incorporating combination of regularization functions with loss functions in SVM classifier to improve classification accuracy by reducing processing time of developed model. Experiment was performed on dataset of 475 MRI scans of 69 patients collected from LITS 2018 Challenge database and by incorporating FE techniques i.e., regularization function, region growing algorithm, weiner filtering, GLCM and watershed method, enhanced SVM based model found superior than other previously used ML techniques with an enhanced accuracy of 98.9%. Oniani D et al. [111], demonstrated use of GNN in cancer classification task by comparing eight GNN models along with five classical ML model on retrieved phenotypic characterizations and genetic features extracted from EHRs & genetic test records collected from Mayo Clinic database. On utilizing frequency threshold, mayo's NLP & UMLS services, multi-hot encoding & scaling method as feature extractor, GNN models specifically chebyshev-graph neural network (ChebNet), graph sample and aggregate (GraphSAGE) & topology-adaptive graph convolutional network (TAGCN) outperformed rest used GNN & ML models during cancer classification process with an accuracy of 90.1%.

5.4. Pancreatic cancer

By sharing 01% of mortalities world-wide in all deaths by all diseases and having contribution of 05% mortality in all mortalities due to all cancer types world-wide, pancreatic cancer (PC) has become sixth-most cause of mortality around the world in year 2020 [1]. Pancreas is responsible for producing important hormones & enzymes for managing blood sugar and digestion in abdomen of human body. PC typically occur due to development of mutation in ducts of pancreas, forming a mass in the pancreas & disturbing the flow of hormones out of pancreas [13]. Smoking habits, diabetes, chronic inflammation & family history of PC may lead to higher probabilities of being affected by PC. Pancreatic ductal adenocarcinoma (PDA) is most common type of PC around the world and it seldom detects in its early stages as its symptoms are discoverable in later stage of PC when it is already spread to nearby organs. Hence accurate diagnosis method is need of an hour and ML techniques could be a good solution for the same due to its accurate & fast diagnosis capabilities [14,15]. Several researchers experimented & developed various ML & DL algorithm on NCBI, TCIA, GSE15471 & GSE28735, SEER, TCGA, ISICDM, NIH, MSD dataset & some other private datasets for early detection of pancreas cancer. CT, MRI, EUS, PET, EHR, Tiff images and genomic sequences are commonly employed modalities in pancreatic cancer diagnosis, as presented in Table 4 [112,113].

Yin J et al. [114], improved performance of SVM-RFE method by using RBF kernel & introducing correlation coefficient for eliminating redundant features in high dimensional data such as gene expression microarray. The method was evaluated on NCBI dataset, containing gene expressions of 32 PC subjects with 54675 features. By optimizing the value of predefined threshold "θ" and penalty coefficient "C", accuracy of 84.56% has been achieved by enhanced SVM-RFE method, which was found more promising than baseline SVM-RFE in PC classification. Li C et al. [115], proposed a SVM based CAD system to discriminate pancreatic mucinous cystic neoplasms (MCN) from serous oligocystic adenomas (SOA) of cystic lesions. Pancreas segmentation was formulated on dual-energy spectral CT scans of 42 Patients privatively collected from Ruijin Hospital, Shanghai-China. Classification

Table 4
Recent methods, dataset, feature extraction techniques, modality and result for pancreatic cancer detection.

Reference	Methodology	Feature Extraction Techniques	Datasets	Modality	Results
Yin J et al. [114],	SVM-RFE	RFE & Correlation Method/Penalty-Coefficient	NCBI Dataset	Genomic	84.56% (Accuracy)
Li C et al. [115],	SVM	PCA/Scaling/One-Hot Encoding/Fisher Score	Self-Procured	CT	93.02% (Accuracy)
Cai J et al. [116],	DCNN	CRF/Watershed Transformation/FCN/HED/Graph-Based Fusion Method	Self-Procured	MRI	0.761% (DSC)
Arslan D et al. [117],	KNN/ANN	ANOVA/Scaling/Automatic (Feature/Kernel)	Self-Procured	Genomic	82.7%/84.6% (Accuracy)
Lv Y et al. [118],	LDM/SVM	FCT/Ranking Method/RFE/Scaling	GSE15471/ GSE28735	Genomic	91.28%/87.50% (Accuracy)
Momeni-Boroujeni A et al. [119],	MNN	Hierarchical K-Means Clustering/Grayscale Conversion/2-D Adaptive Noise-Removal/Bimodal Size Distribution Thresholding	Self-Procured	TIFF	77% (Accuracy)
Song Y et al. [120],	LR/SVM/RF/DL	Imputation/Cox Regression/Scaling	SEER	EHR	81.5%/80.7%/81.5%/81.6% (Accuracy)
Chen K et al. [121],	DT/RF/SVM/LR/NN	Power Doppler Flow Imaging/Fisher's Exact Test	Self-Procured	EHR & EUS	0.923%/0. 984/0.923/0.938/ 0.967 (Sensitivity)
Li S et al. [122],	RF/NB/SVM/KNN/EL/ HFB-SVM-RF	DT-PCA/SLIC Clustering/GIM	Self-Procured/ NIH Dataset	PET/CT	90.03%/86.38%/87.72%/ 84.13%/87.65%/96.47% (Accuracy)
Linda CC et al. [123],	DCNN	Data Augmentation/Automatic (Kernel/Filter)	Self-Procured	CT	87.8% (Accuracy)
Hussein S et al. [124],	SVM/RF	K-means Clustering/N4 Bias Feld Correction/Curvature Anisotropic Filter/Cropping/Gist/VGG	Mayo-IPMN	MRI	84.22%/81.96% (Accuracy)
Kuwahara T et al. [125],	ResNet50	Automatic (Filter/Kernel)/Swish & Softmax/Data Augmentation/Cropping/SGD	Self-Procured	EUS	94% (Accuracy)
Zi-Mei Z et al. [126],	SVM/DT/LR/RF/NB/ Bayes Net	REO/mRMR/IFS	TCGA/GEO_573	Genomic	97.53%/96.91%/96.91%/ 96.6%/96.14%/95.83% (Accuracy)
Sekaran K et al. [127],	CNN	GLCM/LBP/LFE/GMM/Cropping/Automatic (Filter/ Kernel)/Data Augmentation	TCIA	CT	99.9% (Accuracy)
Sadewo W et al. [128],	TWSVM (Linear/ Polynomial/RBF Kernel)	Scaling/Imputation/One-Hot Encoding	Self-Procured	EHR	92%/80%/98% (Accuracy)
Tonozuka R et al. [129],	CNN	Data Augmentation/Automatic (Kernel/Filter)/Grad-CAM	Self-Procured	EUS	0.94 (AUROC)
Ke Si et al. [113],	FEE-DL (ResNet34)	Manual Labelling/Data Augmentation/ResNet18/U-Net32/Fusion	Self-Procured	CT	82.7% (Accuracy)
Zhang Y et al. [130],	Hybrid DCNN	Multi-Atlas Based Image Registration/Joint 3D+2D-CNN/ ReLU & Max-Pooling/Cross-Entropy Loss Function/FCM	ISICDM, NIH, MSD	CT	0.82 (Dice Score)

CRF - Conditional random field, HED - Holistically-nested edge detection, LDM - Large margin distribution machine, FCT - Fold change threshold, GSE - Gene sequence expression dataset, MNN - Multilayer perceptron neural network, Tiff - Tag image file format, HFB - Hybrid feedback, DT-PCA - Dual threshold principal component analysis, SLIC - Simple linear iterative clustering, GIM - Gray interval mapping, Gist – Radiologist, IPMN - Intraductal papillary mucinous neoplasm, SGD - Stochastic gradient descent, REO - Relative expression orderings, IFS - Incremental feature selection, LFE - Lump feature extraction, GMM - Gaussian mixture model, TWSVM - Twin SVM, Grad-CAM - Gradient-weighted class activation mapping, FEE-DL - Fully End-to-End DL, ReLU - Rectified linear unit.

accuracy of 93.02% was achieved by designed system incorporating feature extraction techniques like PCA, scaling, one-hot encoding, fisher score method etc.

Cai J et al. [116], developed conditional random field (CRF) framework-based CAD system to classify & segment pancreatic cancer by combining graph-based decision fusion process with DL-based classifier named CNN. PC segmentation was evaluated on self-procured dataset of 78 abdominal MRI scans, collected from Dept of Biomedical Engineering, University of Florida, Gainesville-USA. By incorporating CRF, WT, FCN, HED and graph-based fusion with the proposed system, DCNN clocked the accuracy of 0.761 (DSC). Arslan D et al. [117], used ANOVA method for elimination & reduction of redundant features from pancreatic cancer gene expression data and evaluated ANN & KNN classifiers on self-procured microarray gene expression dataset containing 52 microarray samples with 54613 features, verified by Mayo institutional review board & deposited in GEO database later on with the accession code 16515. Experiment score recognized ANN superior than KNN with an accuracy of 84.6% during diagnosis of pancreatic cancer.

Lv Y et al. [118], proposed a classification method by combining RFE-SVM and LDM-RFE to diagnose pancreatic cancer. Along with FCT, ranking Method, RFE, scaling methods, SVM & LDM were evaluated on GEO database of 84 pairs of pancreatic ductal carcinoma in genomic modality, collected jointly from GSE15471 & GSE28735 datasets. Classification results showed superiority of LDM-RFE over SVM-RFE with an enhanced accuracy of 91.28% due to optimal searching & selection of PC biomarker using RFE technique. Momeni Boroujeni A et al. [119], designed a FNA biopsy-based system for the diagnosis of solid pancreatic tumor. Along with hierarchical KNN, grayscale conversion, 2-D adaptive noise-removal filter & thresholding methods, a MNN was evaluated on 277 tiff images of 75 pancreatic FNA cases acquired using ThinPrep laboratory information system from SUNY Downstate Medical Center, Brooklyn-New York. The proposed method acquired accuracy of 77% during the classification of pancreatic cancer.

Song Y et al. [120], proposed ML-based predictive model for detection of pancreatic cancer by selecting best classifier out of LR, SVM, RF and DL. Using imputation, cox regression & scaling method during feature extraction process, all four utilized ML classifiers were benchmarked on EHR of 3944 cases of pancreas neuroendocrine tumors (PNETs) extracted from SEER database. DL model with an accuracy of 81.6% outperformed rest of the ML classifiers during classification of PC. Chen K et al. [121], developed ML-based vascular architecture (VA) classification for evaluation & classification of pancreatic neuroendocrine tumor (PNET) in EUS modality. Five commonly used ML classifiers named DT, RF, SVM, LR & NN were examined on private dataset of 112 EUS of PNET cases collected from Department of Endoscopy, Fudan University Shanghai Cancer Center, Shanghai-China along with Power doppler flow imaging and Fisher's exact test. With an sensitivity of 0.984 & 0.967 respectively, RF & NN based systems were found superior than rest of the utilized classifiers during PNET classification task.

Li S et al. [122], proposed a HFB-SVM-RF based system for the diagnosis of pancreas cancer using PET/CT modality by stacking up segmentation, feature selection & classification processes. Five ML techniques i.e., RF, NB, SVM, KNN & ensemble learning (EL) were evaluated & compared with proposed hybrid model on dataset of 1782 PET/CT scans from 80 subjects, collected from General Hospital of Shenyang Military Area Command, Shenyang-China & NIH Clinical Center. FE techniques utilized were DT-PCA, SLIC and GIM. Observed outcomes signified superiority of proposed HFB-SVM-RF based system over other used ML methods, with an impressive accuracy of 96.47%, during diagnosis of PC. Linda CC et al. [123], developed a DL-based model for early detection of pancreatic cancer specifically pancreatic adenocarcinoma (PDAC) using CT modality. DCNN was evaluated on 1325 CT scans (575 healthy & 750 PDAC patients) procured from Department of Radiology and Radiological Science, Johns Hopkins University School of Medicine, Baltimore-Maryland along with data augmentation and filter-based automatic FE techniques and achieved segmentation accuracy of 87.8%.

Hussein S et al. [124], proposed novel supervised and unsupervised ML-based strategies to stratify & classify pancreatic tumor from IPMN using SVM & RF-based model. Experimentation was performed on 171 T^2 MRI (38 normal & 133 IPMN) Scan extracted from Mayo Clinic, Jacksonville. Both models were evaluated by multiple experiments using different features set i.e., radiologist, VGG-fc7 & VGG-fc8 and utilizing FE techniques i.e., K-means clustering, N4-bias field correction, curvature anisotropic filter, cropping & VGG. SVM-based model achieved 84.22% accuracy when combined with VGG-fc8 feature set & RF-based one received 84.18% accuracy in case of VGG-fc7 feature set, showing the superiority of transfer learning-based FE methods over manual FE by radiologist. Kawahara T et al. [125], investigated DL-based method for diagnosis & prediction of pancreatic cancer using EUS scans of IPMNs. ResNet50-based DL algorithm with swish & softmax activation function along with data augmentation, cropping, SGD optimization techniques, were employed on 3970 EUS images of 206 patients, self-procured from Aichi Cancer Center Hospital, Nagoya-Japan and clocked the accuracy of 94% during the detection of malignancy in IPMNs.

Zi-Mei Z et al. [126], designed novel ML-based approach by examining multiple classifiers i.e., SVM, DT, LR, RF, NB & Bayes Net, incorporated with REOs to detect diagnostic signature of PDAC at early stage using microarray gene expression & RNA sequence data. Along with REOs, mRMR & IFS techniques, all utilized classifier were evaluated on gene expression set 573 PDAC & RNA sequences of 177 PDAC samples, extracted from GEO & TCGA dataset respectively. Experiment outcome identified SVM as best algorithm to detect early stage PDAC biomarkers with a classification accuracy of 97.53%. Sekaran K et al. [127], suggested DL-based methodology by combining CNN & GMM with expectation-maximization (EM) algorithm for prediction of pancreatic tumor using of CT scans. Apart from GMM, GLCM, LBP, LFE & Lump recognition (LR) algorithms, cropping & data augmentation techniques were utilized as feature extractor during experimentation. The proposed model hit 99.9% accuracy on dataset of 19,000 CT scans of 82 PC patients, collected from TCIA repository.

Sadewo W et al. [128], proposed a TWSVM-based ML method for detection of early-stage pancreatic cancer using EHR data modality. Linear, polynomial & RBF kernels were investigated during different experiments using TWSVM classifier over dataset of 203 EHR samples of PC subjects, privately obtained from Al Islam Hospital, Bandung-Indonesia, along with basic scaling, imputation & One-Hot encoding methods. Observed results signified dominance of RBF kernel in TWSVM with an accuracy of 98% during classification of PC. Tonozuka R et al. [129], developed a DL-based CAD system for detection of PDAC using EUS scans of patients. CNN was employed as classifier along with data augmentation, filter-based segmentation & Grad-CAM techniques during study. Dataset used contained 1190 EUS scans of 139 patients, which were self-procured from Endoscopic Center, Tokyo Medical University, Tokyo-Japan. The developed CAD system proved to be efficient enough for identification of PDAC with an achieved accuracy of 0.94 (AUROC).

Ke Si et al. [113], proposed a FEE-DL model to diagnose pancreatic cancer at initial stage using CT scans of patients. FEE-DL stacked up pancreas localization, segmentation, and tumor diagnosis tasks together and by incorporating manual labeling by radiologists, data augmentation, ResNet18, U-Net32 & fusion techniques, FEE-DL detected classification accuracy of 82.7% using ResNet34 architecture. Dataset utilized for evaluation consist of 143,945 CT scans of 319 PC patients, which were privately procured from Zhejiang University School of Medicine, Zhejiang-China. Zhang Y et al. [130], proposed a hybrid DCNN-based segmentation pipeline, embracing both 3D level-set & multi-atlas registration along with 3D-patch based CNN & 2D slice-based CNN, to segment pancreatic tumor from CT scans. Proposed pipeline consisted of three stages, referred as coarse, fine & refine stage. ReLU activation, max-pooling, cross-entropy & dice coefficient-based loss function & FCM-based edge detection techniques were used with hybrid DCNN model during segmentation course. Proposed model was evaluated on dataset of 399 CT scans collected from three public dataset named ISICDM 2018, NIH & MSD and achieved accuracy of 0.83% (DSC).

5.5. Brain cancer

Bearing portion of 0.44% in mortalities world-wide in all deaths by all diseases and having contribution of 03% mortality in all mortalities due to all cancer types world-wide, brain cancer has become eighth-most cause of mortality around the world in year 2020 [1]. Abnormal & irregular growth of brain cell may lead to mutation in brain cell's DNA & might leads development of mass or tumor in human brain. This mass could affect nervous system's functions up to an extent, however location & growth rate of mass only determine its severity on nervous system. Gliomas & meningioma's are most common form of brain tumor that exists. Brain cancer has four categories. Grade-1 & grade-2 tumor generally has swallow-pace growth & falls under benign category, however grade-3 & grade-4 tumor has speedy growth & fall under malignant or cancerous category [16,131]. Pre-processing phase of ML play important role in brain cancer diagnosis process as noise & non brain tissues removal is must for accuracy enhancement [132]. Several researchers developed & applied several ML & DL algorithm on BraTS 2015, 2016, 2017, ISLES 2015, Radiopaedia, Figshare, TCGA-GBM datasets & some other private datasets for early detection of brain cancer. MRI, FMRI & diffusion tensor imaging (DTI) are commonly employed modalities in brain cancer diagnosis, as shown in Table 5 [133,134].

Kamnitsas K. et al. [135], presented a deep multiscale 3D-CNN model named "DeepMedic" for brain cancer segmentation using MRI scans for improving brain cancer diagnosis. The model was trained on 274 MRI scans taken from BRATS 2015 dataset & evaluated on 191 scans of 94 subjects collected from BRATS 2016 dataset. By applying basic mean & standard deviation-based normalization, data augmentation & automatic kernel-based FE techniques, proposed model acquired segmentation accuracy of 89.6%. Nie D et al. [133], proposed a SVM based method for prognosis of brain cancer patients by inducing automatic FE of multi-modal pre-operative brain images of high-grade glioma (HGG) patients. 3D-CNN, SIFT, 10-fold CV were utilized as FE techniques along with SVM model for prognosis process. Proposed model was evaluated on MRI, FMRI & DTI scans of 69 HGG patients, self-procured from Department of Radiology, University of North Carolina, Chapel Hill-USA. Proposed SVM-based prognosis model received an accuracy of 89.9%.

Sérgio P et al. [136], proposed a DL-based segmentation method using CNN architecture for automatic segmentation of brain tumor from MRI scans of patients with gliomas. Proposed CNN model along with FE techniques i.e., bias field correction, intensity & patch-based Nyúl normalization method, data augmentation, categorical cross-entropy & Relu activation function, was evaluated on 304 MRI scans of brain tumor patients retrieved collectively from BRATS 2013 & 2015 challenge

Table 5
Recent methods, feature extraction techniques, dataset, modality and result for brain cancer detection.

Reference	Methodology	Feature Extraction Techniques	Datasets	Modality	Results
Kamnitsas K. et al. [135],	3D-CNN	Data Augmentation/Mean-based Normalization/Automatic (Kernel/Filter)	BRATS 2015	MRI	89.6% (Accuracy)
Nie D et al. [133],	SVM	SIFT/3D-CNN/10-fold CV	Self-Procured	MRI/FMRI/DTI	89.90% (Accuracy)
Sérgio P et al. [136],	CNN	Bias field correction/Intensity & Patch-based Nyúl Normalization/Data Augmentation/Categorical Cross-entropy/Relu	BRATS-2013/BRATS 2015	MRI	0.88 (DSC)
Wasule V and Sonar P. [137],	SVM/KNN	GLCM/Median Filter/Power Law Transformation/Morphological filtering	Self-Procured/BRATS 2012	MRI	85%/72.5% (Accuracy)
Fidon L et al. [138],	ScaleNets (CNN)	Automatic (Kernel/Filter)/Factorisation of the feature space	BRATS-2015	MRI	88% (Accuracy)
Abbasi S and Tajeripour F. [139],	RF	OSTU Thresholding/LBP-TOP/HOG -TOP	BRATS-2013	MRI	0.93 (DSC)
Javeria Amin et al. [134],	RF	GWF/HOG/LBP/SFTA	BRATS-2012/BRATS-2013/BRATS-2014/BRATS-2015/ISLES 2015	MRI	98.9%/91.0%/95.0%/92%/93.3% (Accuracy)
Myronenko A. [140],	Autoencoder-CNN	Group Normalization (GN)/ReLU & Sigmoid/Adam Optimizer/L2-Norm Regularization/Data Augmentation	BRATS-2018	MRI	0.884 (DSC)
Mostefa B.N et al. [141],	EnsembleNet-CNN/2CNet-CNN/3CNet-CNN	Fusion Function/ReLU & Sigmoid/Adam, RMSprop & SGD Optimizer	BRATS-2017	MRI	0.89/0.88/0.87 (DSC)
Iqbal S et al. [142],	CNN/LSTM/Ensemble (CNN + LSTM)	GF/HE/USM/ReLU/Adam Optimizer/Categorical Cross-Entropy	BRATS 2015	MRI	0.75/0.81/0.82 (DSC)
Sajjad M. [143],	InputCascadeCNN	N4ITK Bias Correction/Connected Components Labelling/Data Augmentation	Radiopaedia/Self Procured	MRI	94.58% (Accuracy)
Mehmood I et al. [144],	SVM	BoW/SURF/Volume Marching Cube Algorithm	Self-Procured	MRI	99% (Accuracy)
Saba T et al. [145],	DT/KNN/Ensemble/LDA/SVM/LR	VGG-19/GrabCut method/LBP/HOG/Features Fusion by Entropy	BRATS -2015/BRATS -2016/BRATS-2017	MRI	98.78%/99.63%/99.67% (Accuracy)
Khan MA et al. [146],	ELM	Edge-Based Histogram Equalization/DCT/VGG16 & VGG19/Feature Fusion	BRATS2015/BRATS2017/BRATS2018	MRI	97.8%/96.9%/92.5% (Accuracy)
Rehman A et al. [147],	CNN/SVM	Contrast Stretching/Data Augmentation/AlexNet, GoogLeNet, VGGNet & GoogleNet Inception/Softmax	Figshare	MRI	98.69%/95.44% (Accuracy)
Rehman A et al. [148],	FNN	Pearson correlation/3D-CNN/VGG19/ReLU & Softmax	BRATS2015/BRATS2017/BRATS2018	MRI	98.32%/96.97%/92.67% (Accuracy)
Díaz-Pernas, F. J et al. [149],	Multi-Scale CNN	Data Augmentation/Pixel Standardization based Scaling/SGD optimizer	Self-Procured	MRI	97.03% (Accuracy)
Ginni, G et al. [150],	Hybrid Ensemble Method (KNN-RF-DT)	SWT/PCA/GLCM/Otsu's Threshold/Majority Voting	TCGA-GBM	MRI	97.31% (Accuracy)

- Modified CNN, TOP -Three Orthogonal Planes, GWF - Gabor Wavelet Features, SFTA - Segmentation Based Fractal Texture Analysis, GN - Group Normalization, RMSprop - Root Mean Squared Propagation, LSTM - Long Short Term Memory, GF - Gaussian Filter, HE - Histogram Equalization, USM – Un-sharp Masking, BoW - Bag of Words, SURF - Speeded Up Robust Features, ScaleNets, AlexNet, GoogLeNet, VGGNet, GoogleNet, Inception - Modified CNN, FNN - Feed-Forward Neural Network, SWT - Stationary Wavelet Transform.

datasets and received accuracy of 0.88 (DSC). Same model was also benchmarked with previously used ML techniques & analysis results determined proposed method superior than others. Wasule V and Sonar P., [137], presented an automatic ML-based methodology for incidence of malignant & benign as well as low-grade glioma (LGG) & HGG during brain tumor classification. SVM & KNN model were utilized along with FE techniques i.e., GLCM, median filter, power law transformation & morphological filtering during experimentation and evaluated on self-procured dataset of 251 MRI scans from clinical database of Sahyandri hospital, Pune. Evaluation results shows dominance of SVM-based model over KNN-based model with accuracy of 85% & 72.5% respectively.

Fidon L et al. [138], proposed a novel scalable multi-modal DL framework for four image modalities (T1, T1c, Flair and T2 MRI) used during segmentation process of brain tumor. The proposed CNN-based model was referred as ScaleNets and evaluated on 274 MRI scans from BRATS 2015 dataset during training & 20 MRI scans of BRATS 2013 dataset during testing phase. Along with automatic extraction, factorisation of the feature space into imaging modalities (M-space) and modality-conditioned features (F-space) were employed during experimentation & clocked 88% accuracy in diagnosis of brain tumor, identifying ScaleNets more scalable & efficient than conventional CNN. Abbasi S and Tajeripour F., [139], suggested an automated ML-based diagnosis system for early-stage brain tumor detection using 3D MRI scans of brain tumor patients. RF algorithm along with FE techniques i.e., Ostu algorithm, LBP-TOP & HOG-TOP method, was employed during detection process & evaluated on BRATS 2013 dataset having 30 MRI scans. Proposed RF-Based model received improved accuracy of 0.93 (DSC) during brain tumor detection process.

Javeria Amin et al. [134], proposed a feature fusion-based ML approach for automatic brain tumor detection using MRI image modality. RF classifier in combination with unsupervised clustering method was employed & evaluated on 639 MRI scans, collected from five public dataset named BRATS-2012, BRATS-2013, BRATS-2014, BRATS-2015 & ISLES 2015. By incorporating FE techniques i.e., GWF, HOG, LBP & SFTA, proposed RF-based model clocked maximum accuracy 98.9% during detection of brain tumor. Andriy Myronenko., [140], suggested a semantic auto-encoder based segmentation system for brain tumor detection for limited size dataset of 3D MRI scans, known as auto-encoder CNN. Suggested model was accompanied with GN, ReLU & Sigmoid activation function, Adam optimizer, L2-norm regularization & data augmentation techniques during experimentation and evaluated on 285 MRI scans of BRATS 2018 challenge's dataset. Proposed model received accuracy of 0.884 (DSC).

Mostefa B,N et al. [141], proposed & developed a novel DL model for early stage brain tumor segmentation by introducing three end-to-end incremental DCNN models referred as EnsembleNet-CNN, 2CNet-CNN & 3CNet-CNN. Filter-based FE along with fusion function, ReLU & Sigmoid activation function, Adam, RMSprop & SGD optimizer were utilized during model development phase and evaluated on 285 MRI scans from BRATS 2017 challenge dataset. By using most influencing hyper-parameters, proposed models outperformed most of state of art ML methods used previously with a received accuracy of 0.89 (DSC), 0.88 (DSC) & 0.87 (DSC) respectively. Iqbal S et al. [142], presented a LSTM & CNN-based DL model for brain tumor segmentation. CNN, LSTM & Ensemble of both model were evaluated on 384 MRI scans collected from BRATS 2015 dataset by incorporating GF, HE & USM techniques along with ReLU activation function, Adam optimizer, and categorical cross-entropy loss function. With a received accuracy of 0.75 (DSC), 0.81(DSC) & 0.82 (DSC) respectively, ensembled model was identifies as more accurate than classical CNN & LSTM-based model during segmentation process.

Sajjad M., [143], proposes a novel CNN-based CAD system called InputCascadeCNN, for classification of multi-grade brain tumor using MRI image modality. Proposed system was found 40-fold efficient than traditional CNN in terms of processing speed. Along with N4ITK bias correction algorithm, connected components labelling algorithm to remove flat blobs & data augmentation methods, InputCascadeCNN was evaluated on 3185 MRI scans collectively retrieved from radiopaedia dataset & self-procured dataset of Nanfang Hospital, Guangzhou-China and achieved convincing accuracy of 94.58% during classification process. Mehmood I et al. [144], developed an intelligent CAD system for analysing & classifying brain MRIs to assist radiologist in correct diagnosis of brain tumor. By incorporating BoW, SURF & Volume marching cube algorithm with SVM-based classification system, proposed CAD system was trained & tested on self-procured dataset of 1100 MRI scans of 30 patients collected from Department of Radiology, Lady Reading Hospital-Peshawar and with a received accuracy of 99%, BoW driven SVM classifier-based framework outperformed regular MRI analysis tools named ITK-SNAP & 3D-Doctor.

Saba T et al. [145], proposed a transfer-learning (TL) based model for accurate & fast classification of brain tumor by supplementing fused features to multiple ML classifiers i.e., DT, KNN, Ensemble, LDA, SVM & LR. Proposed model was supplemented with VGG, GrabCut method, LBP, HOG & entropy based fusion technique & evaluated on three public datasets named BRATS 2015, BRATS 2016 & BRATS 2017 containing 274, 274 & 285 MRI scans respectively. With a classification accuracy of 98.78%, 99.63% & 99.67% respectively, proposed model found superior than other DL-based model previously used by researchers on the above said datasets. Khan MA et al. [146], proposed an automated DL-based multi-modal classification method for brain tumor detection. This ELM-based model utilized two TL architecture named VGG19 & VGG16 along with edge-based histogram equalization (HE), DCT & partial-least-square (PLS)-based fusion technique for FE & selection. Proposed model was tested on BRATS 2015, BRATS 2017 & BRATS 2018 comprising 274, 285 & 285 MRI scans respectively and achieved accuracy of 97.8%, 96.9% & 92.5% respectively during classification.

Rehman A et al. [147], proposed a DCNN-based framework for automatic classification of brain tumor by incorporating transfer learning model to it. Three TL architecture AlexNet, GoogLeNet & VGGNet along with contrast stretching algorithm and data augmentation method were utilized as feature extractor in proposed deep learning framework and also benchmarked with SVM-based classifier. Model evaluation was done on 3064 MRI scans of 233 Patients collected from public database named Figshare and with a promising accuracy of 98.69%, DCNN-based model outperformed SVM-based model as well as previously used deep learning models in classification of brain tumor task on same dataset. Rehman A et al. [148], designed a novel 3D-CNN based approach for classification & detection of microscopic brain tumor using MRI image modality. Pearson correlation, VGG19, ReLU & Softmax activation function were utilized during feature selection & extraction phase of training & finally classification result of model were validated via FNN. Experiment was performed on BRATS 2015, BRATS 2017 & BRATS 2018 challenge dataset having 274,285 & 285 MRI scans respectively, and achieved accuracy of 98.32%, 96.97% & 92.67% respectively during classification.

Díaz-Pernas F J et al. [149], presented a fully automatic, multi-scale CNN-based method for classification of three brain tumor types i.e., meningioma, glioma & pituitary using 2D-MRI modality. Proposed CNN architecture was supplemented with data augmentation, pixel standardization-based scaling & SGD optimizer and benchmarked on dataset of 3064 MRI scans of 233 patients collected from Nanfang Hospital, Guangzhou-China. With a promising accuracy of 97.03%, proposed method was found better than previously used CNN based approaches on same dataset. Ginni G et al. [150], proposed a hybrid ensemble classifier-based model for detection & classification of brain tumor using MRI modality. This majority voting-based method utilized ensemble of KNN, RF & DT classifiers along with FE methods i.e., SWT, PCA, GLCM & Otsu's threshold during experimentation. Proposed method was evaluated on 2556 MRI images of patients retrieved from public database named TCGA-GBM and with an improved accuracy of 97.31%, proposed hybrid ensemble-based classifier outperformed other utilized traditional individual ML classifier i.e., SVM, NB, DT, NN & KNN during classification process.

5.6. Skin cancer

On accounting 0.23% in mortalities world-wide in all deaths by all diseases and having contribution of 1.35% mortality in all mortalities due to all cancer types world-wide, skin cancer has become tenth-most cause of mortality around the world in year 2020 [1]. Melanoma, basal-cell carcinoma & squamous-cell carcinoma are most common type of skin cancer, which could be precancerous lesions or newly grown abnormality in skin cells mostly due to exposure of skin to UV rays from sunlight. UV radiation exposure, family history of skin cancer, history of sunburn & abnormal moles in the body are well known cause of skin cancer worldwide [151,152]. Early diagnosis of skin cancer needs efficient & most correct methodology to process dermoscopy of epiluminoscopy images & hence ML techniques found to be best alternate for the same. Several ML & DL algorithm has been developed by researchers around the world & applied on PH2, DermIS, DermQuest, DermNet, ISBI, ISIC, TCGA-SKCM, Mednode, MITOS datasets & some other private datasets for early detection of skin cancer. Dermoscopic (DY) images & Genomic are commonly employed modalities in skin cancer diagnosis, as presented in Table 6 [21,153,154].

Bareiro Paniagua LR et al. [155] proposed a ML-based diagnostic system for detection of benign or malignant skin cancer using DY modality. Proposed system was equipped with SVM as classifier and Otsu algorithm, ABCD rule, Inpainting techniques, median filter, contrast limited adaptive histogram equalization (CLAHE) technique as feature extractor. Described SVM-based model was evaluated on self-procured dataset of 104 DY images collected from Faculty of Sciences, Universidad Central de Venezuela and received an accuracy of 90.63% during classification process. Premaladha et al. [156], proposed a novel CAD system based on hybrid supervised ML & DL algorithm to predict & classify melanoma type skin cancer using patient's DY images. DNN, hybrid AdaBoost (SVM-AdaBoost), SVM, adaptive neuro-fuzzy inference system (ANFIS) were utilized as predictor along with FE techniques i.e., Median filter, CLAHE, GLCM, PCA and normalised Otsu's Segmentation (NOS). The proposed system was benchmarked on nearly 992 DY images collected from two public repositories named Mednode & PH2 and experimentation results showed superiority of DNN over other used methods with a received classification accuracy of 92.68%.

Shoieb DA et al. [157], introduced an automated & enhanced DL-based CAD system to diagnose skin cancer using DY images of patients. By utilizing CNN architecture with Median filter, Gabor filters & K-mean clustering technique as a feature extractor, proposed method made use of SVM as classifier for diagnosis task. Derived model was

Table 6
Recent methods, feature extraction techniques, dataset, modality and result for skin cancer detection.

Reference	Methodology	Feature Extraction Techniques	Datasets	Modality	Results
Bareiro Paniagua LR et al. [155],	SVM	Otsu Thresholding/ABCD Rule/Inpainting/ Median Filter/CLAHE Method	Self-Procured	DY	90.63% (Accuracy)
Premaladha, J and Ravichandran KS. [156],	DNN/Hybrid AdaBoost (SVM-AdaBoost)/SVM/ANFIS	Median filter/CLAHE Method/GLCM/PCA/ NOS	Mednode/PH2	DY	92.68%/91.73%/ 90.44%/90.39% (Accuracy)
Shoieb DA et al. [157],	SVM	CNN/Median filtering/Gabor filters/K-mean Clustering	DermIS/DermQuest/ DermNet	DY	93.75%/94.12%/ 98.04% (Accuracy)
Waheed Z et al. [158],	SVM	GLCM/Uniform HSV Conversion	PH2	DY	96%(Accuracy)
Pour MP et al. [159],	CNN	Data Augmentation/FCN-AlexNet/VOC-FCN8s/SGD	ISBI 2016	DY	99% (Accuracy)
Ozkan IA and Koklu M. [153],	ANN/SVM/KNN/DT	ABCD Rule/10-fold Cross-Validation	PH2	DY	92.5%/89.5%/82%/ 90% (Accuracy)
Dorj UO et al. [160],	ECOC- SVM	AlexNet/Cropping,	Self-Procured	DY	94.2%(Accuracy)
Seung SH et al. [161],	CNN	ResNet-152/Gradient-Based Localization	Asan/Med-Node/ Edinburgh/Hallym	DY	0.91 (AUC)
Li Y and Shen L. [162],	FCRN-88	CNN/Data Augmentation/Cropping/LICU/ LFN/LIN	ISIC 2017	DY	85.7% (Accuracy)
Aima A and Sharma AK. [163],	CNN	Thresholding Method/Erosion & Dilation/RGB to HSV Conversion/SGD optimizer	ISIC	DY	74.76% (Accuracy)
Tan TY et al. [164],	SVM-Ensemble/KNN-Ensemble	GLRLM/LBP/HOG/PSO	PH2/Dermofit	DY	97.79%/97.54% (Accuracy)
Saba T et al. [165],	MLP-NN	FlLpF/CNN/HD/Inception V3/Data Augmentation	PH2/ISBI 2016/ISBI 2017	DY	98.4%/95.1%/94.8% (Accuracy)
Jinnai S et al. [166],	FRCNN	Data Augmentation/Oversampling/VGG-16/ SGD	Self-Procured	DY	91.5% (Accuracy)
Zhang N et al. [167],	CNN	WOA	Dermquest/DermIS	DY	96% (Accuracy)
Ashraf R et al. [168],	AlexNet	K-mean Clustering/Gaussian kernels/Data Augmentation/Max pooling/SoftMax Optimizer	DermIS/DermQuest	DY	97.9%/97.4% (Accuracy)
Al-Obeidat F et al. [63],	Cascading classifier (CatBoost algorithm/SVM/RF/MLP)	Discrete Filtering/BABC/Synthetic Minority Oversampling/TMM,	TCGA-SKCM	RNA Sequence	89.9% (Accuracy)
Nofallah S et al. [169],	ESPNet/DenseNet	Watershed-based Segmentation/Padding/Data Augmentation/Oversampling/ADAM Optimizer	Self-Procured/MITOS	DY	98.4%/98.8% (Accuracy)
Saravana Kumar NM et al. [154],	RF/SVM/DenseNet-161	Median filter/Gaussian filter/CLAHE Method/ Thresholding/GLCM	ISIC 2018	DY	85.70%/91.20%/ 96.30%(Accuracy)

ABCD -Asymmetry, border, color, diameter, Mednode - Melanoma diagnosis system using non-dermoscopic images, DermIS - Dermatology information service, HSV - Hue, saturation and value, FCN-AlexNet & VOC-FCN8s – Pre-trained CNN, ECOC - Error-correcting output codes, FCRN - Fully convolutional residual networks, LICU - Lesion indexing calculation unit, LFN - Lesion feature network, LIN - Lesion indexing network, GLRLM - Gray level run length matrix, PSO - Particle swarm Optimization, FlLpF - Fast local laplacian filtering, HD - Hamming distance, FRCNN - Faster region-based CNN, WOA - Whale optimization algorithm, BABC - Binary artificial bee colony, ESPNet - Efficient spatial pyramid of dilated convolutions, DenseNet - Densely connected convolutional networks.

experimented on 337 DY images of skin lesions collected from three public datasets named DermIS, DermQuest and DermNet and received promising accuracy of 98.04% during experimentation & classification phase. Similarly, Waheed Z et al. [158], presented an efficient ML-based model for detecting skin cancer from DY images of patients with the aim for early diagnosis of skin cancer. In the proposed model SVM classifier was trained & tested on 200 DY images retrieved from public dataset PH2 and classifier was supplemented with GLCM & uniform HSV color space method for feature extraction purpose. With a received accuracy of 96%, proposed scheme was found more promising than other ML method used in past by researchers.

Pour MP et al. [159], demonstrated the efficiency of DL-based model in automatic segmentation of skin cancer using patient's DY images. Proposed CNN-based model utilized pre-trained TL-based models named FCN-AlexNet & VOC-FCN8s, data augmentation method & SGD method for feature extraction and evaluated on 1279 DY images of ISBI 2016 Challenge dataset. With a received accuracy of 99%, proposed segmentation approach outperformed 2nd best algorithm of ISBI 2016 challenge. Ozkan IA and Koklu M., [153], proposed a ML-based decision support system to assist radiologist for easy & efficient diagnosis of skin cancer using DY images of patients. Four classifiers named ANN, SVM, KNN & DT, which were supplemented with ABCD rule-based feature extraction, were evaluated on 200 DY images of patients retrieved from PH2 public database. With a classification accuracy of 92.5%, 89.5%, 82% & 90% respectively, ANN with 10-fold CV outperformed rest of used classifier during experimentation.

Dorj UA et al. [160], proposed a DL-based classification model to diagnose skin cancer using DY images of four skin cancer types named actinic keratosis, squamous cell carcinoma, Basal cell carcinoma & Melanoma. Proposed approach utilizes ECOC-SVM as classifier, pre-trained AlexNet along with basic cropping method as feature extractor during model evaluation phase. Developed model was tested & trained on 3753 skin lesion images collected online from different related websites & achieved accuracy of 95.1% during classification task. Seung SH et al. [161], developed DL-based model for classification of 12 different skin diseases into benign & malignant category using DY images. CNN was used as classifier by making use of TL methodology. ResNet-152 and Gradient-based localization were utilized as feature extractor during experiment and proposed model received an average accuracy of 0.91 (AUC) during evaluation performed on 19,398 DY images retrieved from multiple public & private repositories i.e., Asan, Med-Node, Edinburgh & Hallym.

Li Y et al. [162], proposed deep learning-based framework for Melanoma type skin cancer detection by incorporating two FCRNs aimed for segmentation & coarse classification task. CNN, data augmentation, cropping method, LICU, LFN & LIN were utilized during feature engineering phase and proposed framework was tested on 2000 skin lesion images of ISIC 2017 dataset. With an accuracy of 85.7% and area under the curve (AUC) value of 0.912, proposed framework outperformed other used frameworks on same dataset during classification task. Aima Aand Sharma AK,. [163]. proposed DL-based approach for early-stage detection of skin cancer using CNN on DY images of skin cancer patients. FE techniques i.e., Erosion-dilation method, RGB to HSV conversion, thresholding & SGD optimizer were accompanied with CNN architecture during model evaluation phase and then tested on 514 DY images collected from ISIC dataset. Proposed approach received accuracy of 74.76% during experimentation, which seems normal according to small dataset used in the study.

Tan TY et al. [164], proposed an intelligent ML-based system for diagnosis of skin cancer using DY images of patients by incorporating feature extraction techniques named PSO, GLRLM, ABCD rule, LBP & HOG with classifiers named SVM & KNN-based ensembles. Proposed model was evaluated on 1500 skin lesion images of patients retrieved from two datasets called PH2 & Dermofit and with a received accuracy of 97.79% under SVM-ensemble and 97.54% under KNN-ensemble, developed models outperformed other baseline classifiers used previously on same datasets. Saba T et al. [165], proposed a DCNN-based CAD system for detection & classification of skin cancer using DY images. Multiple classifiers i.e., MLP-NN, DT, SVM & KNN were evaluated on total of 4229 DY images collectively retrieved from three public datasets named PH2, ISBI 2016 & ISBI 2017. Finally the best classifier MLP-NN was utilized along with feature extractor i.e., FlLpF, HD-fusion, pre-trained Inception V3 architecture & data augmentation during experiment and received accuracy of 98.4% on PH2, 95.1% on ISBI and 94.8% on ISBI 2017 dataset.

Jinnai S et al. [166], developed DL-based classification system for skin cancer detection using pigmented skin lesions of skin cancer patients. A FRCNN was utilized as classifier along with FE techniques i.e., data augmentation, oversampling, pre-trained VGG-16 model & SGD-based optimization during training phase of experiment. Proposed system was evaluated on 5846 pigmented skin lesion images of 3551 patients self-procured from National Cancer Centre, Tokyo-Japan and with an achieved classification accuracy of 91.6%, proposed system found at par of radiologist performance on same validation data. Zhang N et al. [167], proposed an optimized CNN-based method for early detection of skin cancer disease using DY images of patients. Proposed method was optimized using advance WOA and feature extraction was achieved by convolution & max-pooling strategy. Proposed method was evaluated on total of 22000 DY images retrieved from two datasets named Dermquest and DermIS and with a received accuracy of 96%, it was found better than other DL-based architecture i.e., Inception V3, ResNet-50/101, VGG-16, AlexNet etc, utilized during comparative study.

Ashraf R et al. [168], suggested a region of interest (ROI)-based system for detection of melanoma type skin cancer with nevus cancer. Proposed system utilizes TL-based CNN architecture named ALexNet as classifier along with k-mean clustering, gaussian kernels, data augmentation, max pooling, SoftMax optimizer. Suggested model was trained & tested on total of 534 clinical images of skin lesion procured from Dermquest and DermIS public repositories and received improved accuracy of 97.4% & 97.9% respectively, which were found better than previously used ML methods. AI-Obeidat F et al. [63], proposed a majority voting-based cascading classifier comprised by CatBoost algorithm, SVM, RF & MLP classifier to detect & classify skin cancer patients using oncogenomics data. This proposed system utilized discrete filtering, BABC optimization, synthetic minority oversampling technique, TMM normalization as feature extractor. On evaluation of proposed method on dataset of 21999 features from 472 RNA Sequence samples collected from TCGA-LUSC-SKCM dataset, accuracy of 89.9% has been achieved by the proposed system.

Nofallah F et al. [169], investigated two CNN-based models named ESPNet & DenseNet for classification of mitosis using whole slide images (WSI) of skin biopsies aiming to aid pathologist's detection performance. During experiment watershed-based nuclei segmentation method, padding, data augmentation, oversampling technique & Adam optimizer were utilized as feature extractor. Model evaluation was done on total of 678 mitoses from 06 WSIs collected from MPATH study, University of Washington and MITOS dataset together. Both model were also compared with ResNet & SuffleNet-based models during experimentation and with an improved accuracy of 98.4% & 98.8%, ESPNet & DenseNet models surpassed rest of CNN-based model in terms of classification accuracy. Saravana Kumar NM et al. [154], proposed a feature fusion-based hybrid DL model using DenseNet161 architecture for detection of skin cancer from DY images of patients. By incorporating median filter & gaussian filter, CLAHE technique, thresholding & GLCM methods as feature extractor, proposed model acquired improved accuracy of 96.30% after evaluating on 1113 skin lesion images selected from ISIC 2018 dataset.

6. Analysis & discussion

Artificial Intelligence methods are well known for their efficiency of handling complex computational problems and large & versatile nature data as well. In the past, AI techniques were used only by some of the large scale & high investment organizations like space agencies, research organizations and weather departments of countries as the high computation requirements of AI could be satisfied by these organisation's computer systems only, but with the advancement of computation hardware in recent past, it is now easier to do hands-on in AI techniques in personal computer also. Therefore, due to availability of such standalone and cloud-based systems, researchers have applied AI methods in different domain to automate decision making process. In the same way many researchers, medical experts & academicians started to apply AI techniques in the field of early-stage medical diagnosis, prognosis & treatment and come up with various solutions for existing hurdles in medical diagnosis.

Earlier, quite some of studies were carried out for the above-said, due to limited numbers of ML techniques available in hand and their low accuracy, but in year 2010, with the introduction of DL, research work by researcher in the medical domain has taken reasonable pace and good numbers of articles bubbled up to publish with a good received accuracy. As per our SLR, this study comprises of top three articles, based on detected accuracy & utilized method novelty, for each year from 2016 to 2021. After having that scrutinised paper in hand, we were able to extract information successfully from papers i.e., methodology used/AI method applied, feature extraction techniques used, dataset/database used, data modality & received accuracy given by applied method. All those extracted attributes were tubulised properly for analysis purpose.

On having all extracted information in tabular form, we start the analysis process to infer some meaningful trend out of tuples of extracted attributes and during the analysis we had multiple analysis bases to analyse upon i.e., utilization ratio of ML & DL-based methods in cancer diagnosis, cancer type wise deployment of different classifiers, participation ratio of feature extraction methods used in study and individual modality's participation during individual cancer type diagnosis.

On the basis of analysis carried out on included 108 articles of past six years (2016–2021), it was found that approx. two third of the articles utilized machine learning based technique during cancer detection and one third of the articles incorporated deep learning-based methods for the same. It shows dominance of ML techniques over DL methods in cancer detection task. It could be due to black-box nature of DL method or higher explain-ability of ML methods as explain-ability of applied methods are more preferable in case of medical diagnosis. Apart from aggregate utilization share of ML & DL method in cancer detection, individual cancer type wise participation of used ML & DL methods has been shown in the Fig. 8 for better clarity.

During the analysis process, when we further expand our search domain on utilization of specific individual classifier in different cancer type detection, it was observed that some of the classifiers i.e., CNN, DNN, DT, Ensemble, KNN, NB, RF & SVM dominate other classifiers i.e., AdaBoost, ANN, ET, LDA & LR. In the above figure we can observe that in case of ML method utilization, SVM-based classifiers are employed and in case of DL methods utilization, CNN-based classifiers are most

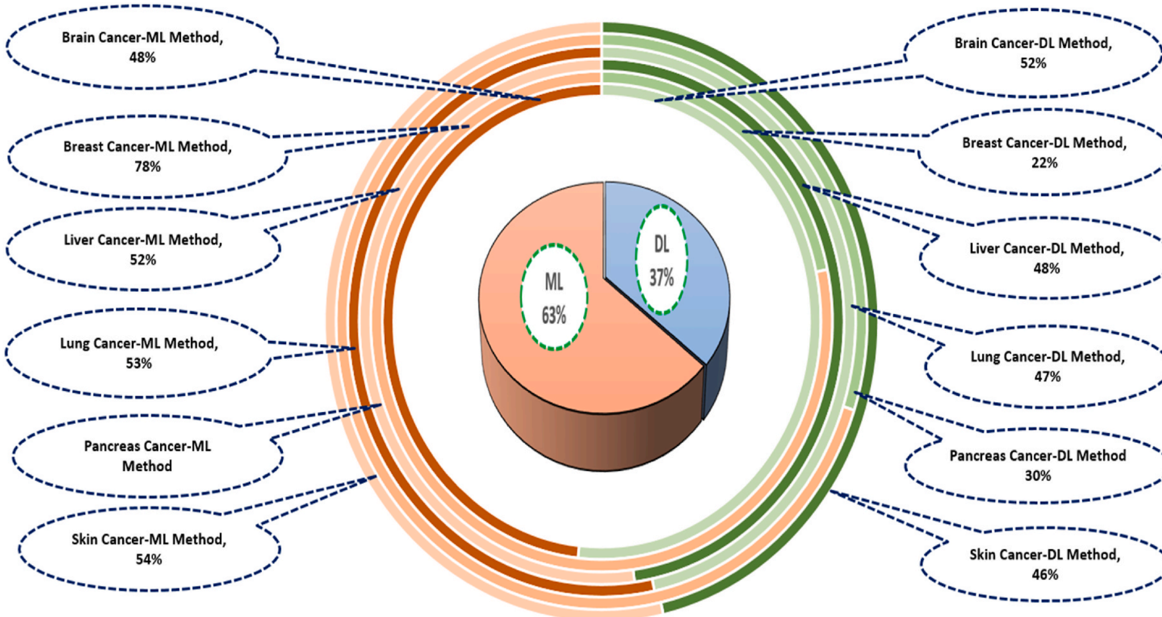

Fig. 8. Overall utilization shares of ML/DL methods in all six-cancer type diagnosis.

preferably used by researchers working in the field of cancer diagnosis, as presented in Fig. 9.

When it comes to utilization of feature extraction (FE) techniques in medical diagnosis domain, there are so many numbers of FE methods possible to use during cancer detection process. Due to large numbers of FE techniques noticed during our literature survey, we have grouped them into multiple general categories on the basis of their task and analysed their utilization percentage in different cancer detection task. As observed in the chart given in the Fig. 10 most of the studies included in this study, incorporated FE methods related to feature normalization, optimization, selection, ROI detection, segmentation & texture detection and only few of them utilized class imbalance control, data labelling & edge detection related methods during feature extraction phase of cancer detection & classification process. It is due to the automatic FE nature of applied deep learning method by researchers, where manual FE is not required.

There are various kinds of medical data modality available to use for cancer detection task i.e., MRI, CT, US, US, DY, PET scans, Genomics & EHR. Different cancer types support different modality. Some studies utilized one type of modality during individual cancer type detection whereas other studies made use of other modality type for the same task. Therefore, common trend line for modality utilization might not be possible. However, by observing above shown chart of modality participation, it could be possible to draw some inference regarding preferred modality type in different cancer type diagnosis. Analysis shows dominance of CT modality (liver, lung & pancreas cancer), MRI modality (brain cancer), MG modality (breast cancer) and DY modality (Skin cancer), as presented in Fig. 11.

Classification accuracy is the most commonly used key performance indicator (KPI) during evaluation of any ML or DL model at the time of medical diagnosis of cancer, there are other KPIs also like DSC, precision, sensitivity, specify, ROC and AUC. Use cases of any of these are totally based on the choice of evaluation basis from observer side on specific type of machine learning task. However, dominance of accuracy KPI, was observed during most of the past studies on cancer diagnosis. Hence our review also considered this KPI as prime & common criteria

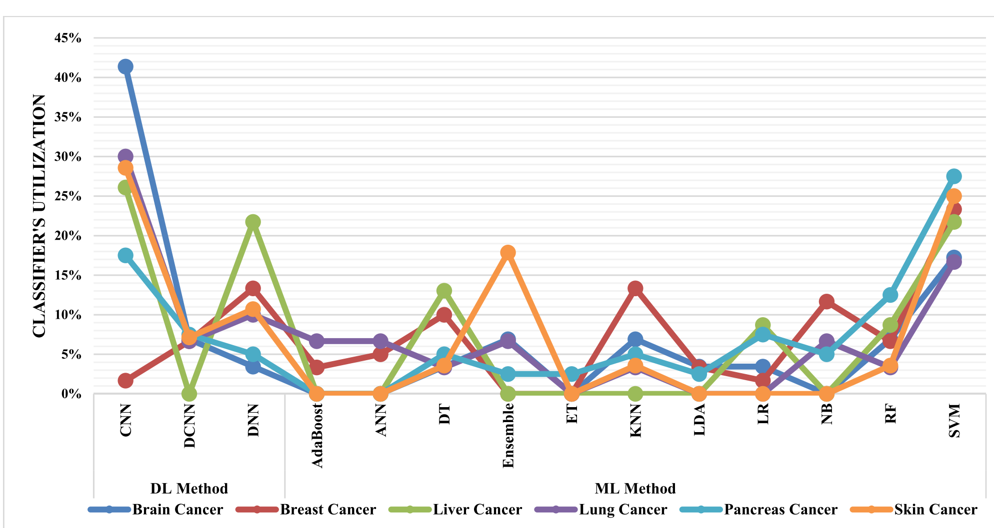

Fig. 9. Utilization shares of various classifiers in all six-cancer type diagnosis.

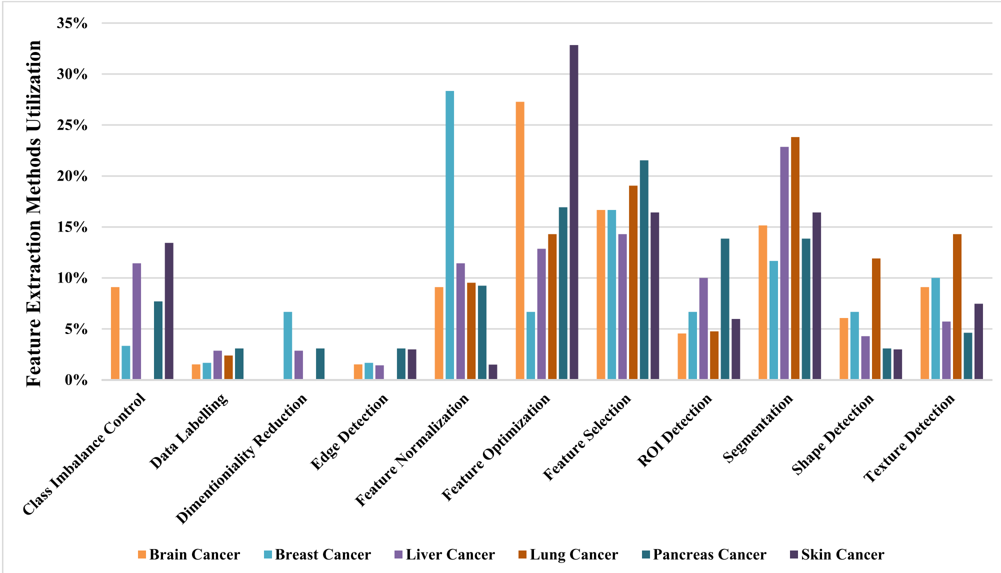

Fig. 10. Utilization shares of various feature extraction methods in individual cancer type diagnosis.

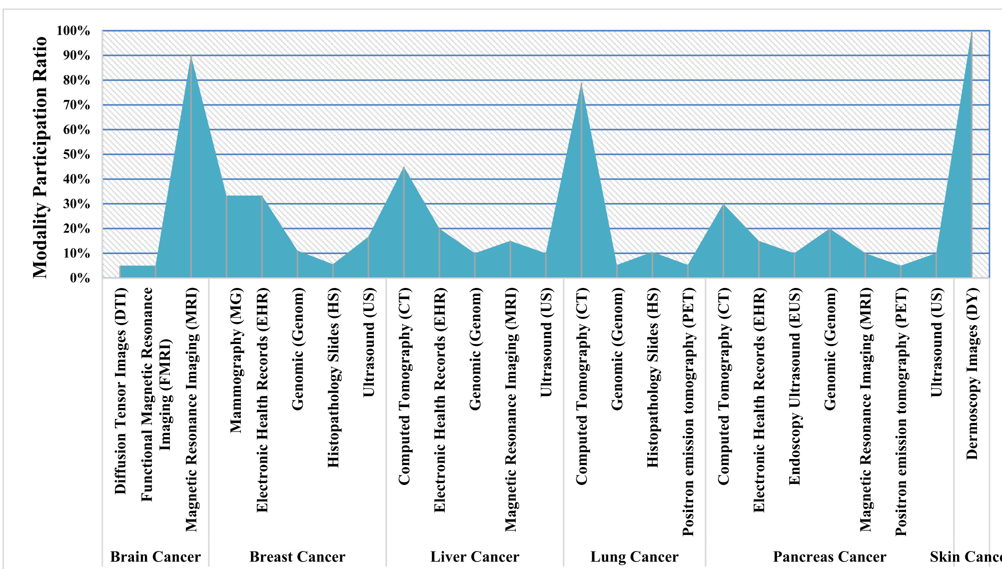

Fig. 11. Individual modality's participation during individual cancer type diagnosis.

for evaluation of ML/DL-based techniques presented in selected articles of this study. Apparent results of our analysis shows that most of the ML/DL-based classifiers were found to be above 98% accurate in cancer detection task, marking them as preferable assisting source to medical personnel like radiologists, clinicians & doctors during disease diagnosis process. We have selected best performing classifiers related to each cancer type detection using received accuracy and observed that most of the time CNN-based DL model & SVM-based ML model is found more accurate in past cancer detection related studies, whereas some studies identified RF & DT classifiers as best predictor of cancer disease, as presented in Fig. 12.

6.1. ANALYSIS summary

This section provides brief cancer type-wise as well as complete case analysis summary of literature review performed in this study.

Table-1 depicts that, in the area of lung cancer diagnosis, most of the studies utilized CNN-based methods i.e., 2d-CNN, DCNN, DBN, FPSO–CNN, DFD-Net etc. [47–50,52,54,55,58,61,62] and only limited number of studies used classic ML-based method i.e., DT, RF, NB, NN, AdaBoost, SVM etc. [46,51,56,57,63] during lung cancer detection task. LIDC-IDRI is found to be most utilized dataset during all of the study considered in this study & other dataset used are TCGA, PD-L1, Anode09, LUNA16 etc. In the similar way, one can notice that Computerized Tomography (CT) modality has dominance in previous studies and highest achieved accuracy of 99.6% is clocked by 2D-ConvNet model in all past studies considered in this paper in regards to lung cancer detection.

Similarly Table 2 shows that, in the area of breast cancer diagnosis, most of the studies utilized state-of-the-art ML-based method i.e., DT, RF, NB, KNN, ET, GB, LDA, SVM etc. [65,70,71,77,78,81–85] and only few studies used CNN-based methods i.e., DBN, DCNN, Inception V3, ResNet-101, etc. [69,72,76,80] during breast cancer detection task. WBCD is found to be most utilized dataset during all of the studies

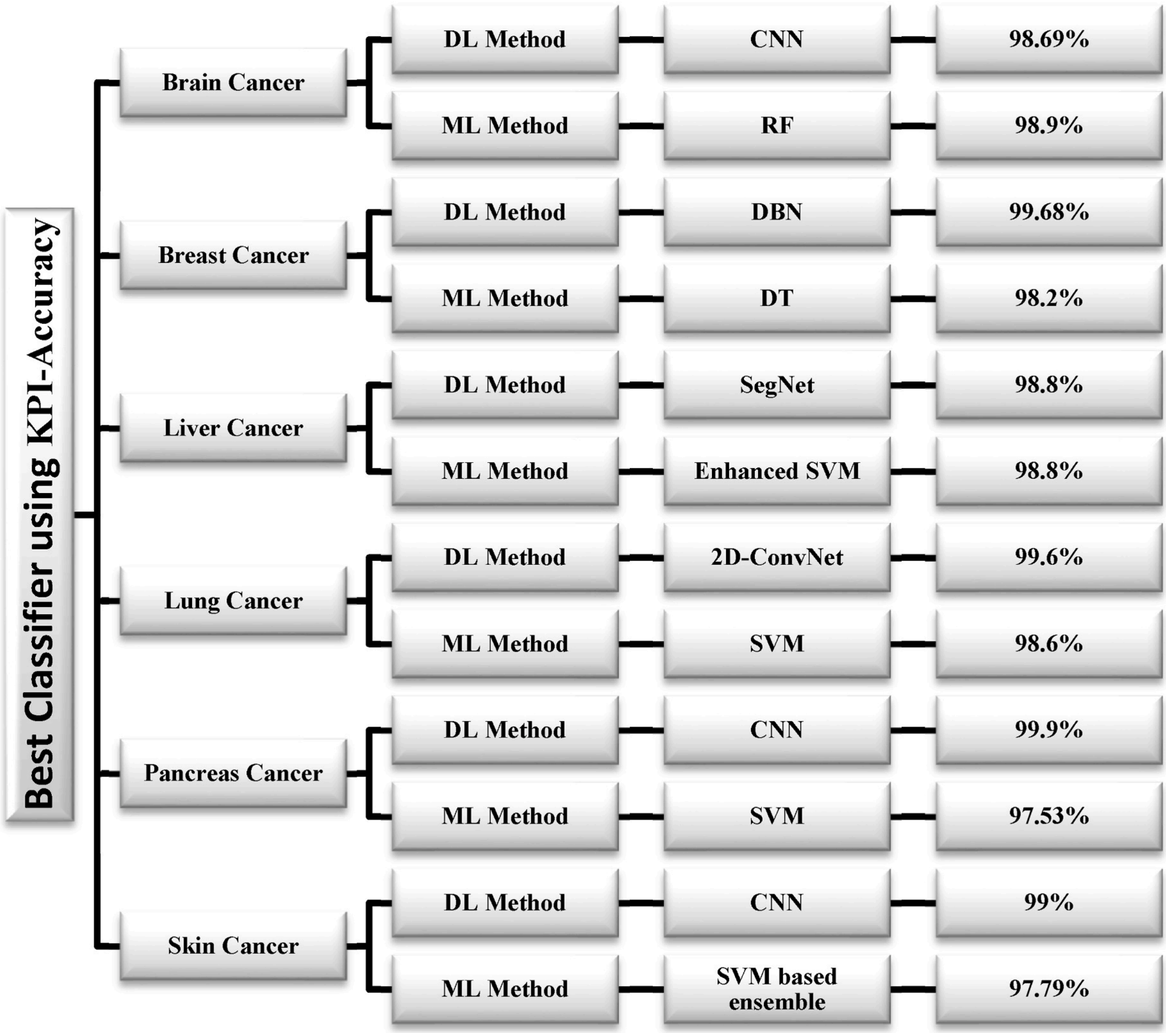

Fig. 12. Best ML/DL classifiers using accuracy.

considered in this review & some other dataset used are DDSM, MIAS, and TCGA-BRCA. We can notice that Mammography (MG) modality is preferable choice in past studies and highest achieved accuracy of 99.68% is clocked by DBN model in all past studies considered in this paper with regards to breast cancer detection.

Table-3 signifies that, in the area of liver cancer diagnosis, we may observe that CNN-based methods i.e., FCN, DNN, SegNet, U-Net, GNN etc. [96,104–108,111] are more preferable than SVM-based methods [94,95,99,108,110] among researchers for liver cancer detection task. Apart from self-procured private datasets, 3D-IRCADB & LITS dataset are mostly used datasets noticed in past studies. We can notice that CT & MRI are the mostly used modalities in past studies and maximum achieved accuracy of 99.8% is reported by SegNet & Enhanced-SVM model in all past studies considered in this paper with regards to liver cancer detection.

Table 4 represents that, in the area of pancreatic cancer diagnosis, we can witness that traditional ML-based methods i.e., LR, NB, KNN, DT, RF, SVM, NN etc. [114,115,118,120–122,124,126,128] are more employed than DL-based model i.e., DCNN, ResNet-50, FEE-DL etc. [113,116,119,123,125,127,129,130] by researchers for pancreas cancer detection task. Apart from self-procured private datasets, TCGA, TCIA & Mayo-IPMN dataset are mostly used datasets observed in recent studies. CT, MRI & Genomic modalities are widely used modalities in past studies and extreme achieved accuracy of 99.9% is recorded by CNN model in all past studies considered in this paper with regards to pancreas cancer detection.

Table 5 describe that, in the area of brain cancer diagnosis, it is worth noticing that CNN-based methods i.e., 3D-CNN, ScaleNet, Multiscale-CNN, LSTM etc. [135,136,138,140–143,147–149], have dominance over ML-based methods i.e., SVM, KNN, DT, LDA, LR [133,137,144,145] among researchers for brain cancer detection task. Apart from self-procured private datasets, BRATS 201X & FigShare dataset are commonly used datasets observed in past studies. We can notice that Magnetic resonance imaging (MRI) is mostly used modality in past studies and maximum achieved accuracy of 98.9% is reported by RF-based model in all past studies considered in this paper with regards to brain cancer detection.

Similarly Table 6 portrays that, in the area of skin cancer diagnosis, CNN-based methods i.e., DNN, FCRN-88, FRCNN, AlexNet, DenseNet etc. [156,159,161–163,166–169], have been utilized more than traditional ML-based methods i.e., SVM, DT, KNN, RF, MLP [153,155–158,160,164] for skin cancer detection task. Apart from self-procured private datasets, PH2, DermIS, DermQuest & ISIC datasets are frequently used datasets noticed in past studies. Dermoscopy (DY) is the mostly used modality in past studies and peak achieved accuracy of 99% is recorded by CNN model in all past studies considered in this paper with regards to skin cancer detection.

It was observed from above cancer type-wise analysis summary that in the area of different cancer type's diagnosis, various state-of-art ML algorithm and DL algorithms had been employed by previous researchers in recent past. SVM-based ML method & CNN-based DL methods were found to be frequently utilized as well as significantly efficient than other utilized ML/DL-based methods for cancer diagnosis task. Moreover, feature extraction techniques i.e., LBP, PCA, HOG and GLCM were utilized most frequently by previous researchers in recent past.

Next section provides brief introduction of most frequently used ML/DL-based methods and feature extraction techniques, by researchers in recent past. This section may provide some glimpse of basic processes of frequently used ML/DL-based techniques and FE techniques, utilized for cancer diagnosis task in recent past, to novice researchers.

6.2. Brief introduction of frequently observed methods

6.2.1. Support vector machine (SVM)

SVM is most preferred machine learning-based classification algorithm because of its ability to produce significant prediction accuracy with a reduced amount of computation power. Finding an optimal hyperplane in an N-dimensional feature space with largest possible margin around decision boundary so as classify data points distinctly, is the key objective of SVM algorithm.

Hyperplane generated by SVM algorithm is a decision boundary, which helps in classification of data point among different classes. Data points on either side of hyperplane may belongs to different classes. Hyperplane's dimension depends on number of features considered for classification of data points i.e., if only two numbers of features are under consideration, then hyperplane drawn is line only and if three numbers of features are considered, then hyperplane will be two-dimensional plane as depicted in Fig. 13. Reasons of SVM popularity lies in its advantages i.e., its efficiency of handling structured as well as unstructured data, its effectiveness in high dimensional spaces, its memory efficiency, its kernel trick for handling complex problems and low risk of overfitting. Apart from above advantages, SVM have some challenges as drawbacks i.e., its inefficiency in case of noisy dataset or target class overlapping scenario, its un-interpretability due to unavailability of probabilistic explanation of resulted classification, its unsuitability for large size datasets and selecting appropriate kernel function & tuning its hyper parameters like penalty-C & gamma is not easy for many users [46,57,63,77,85,99,110,133,145,155,164].

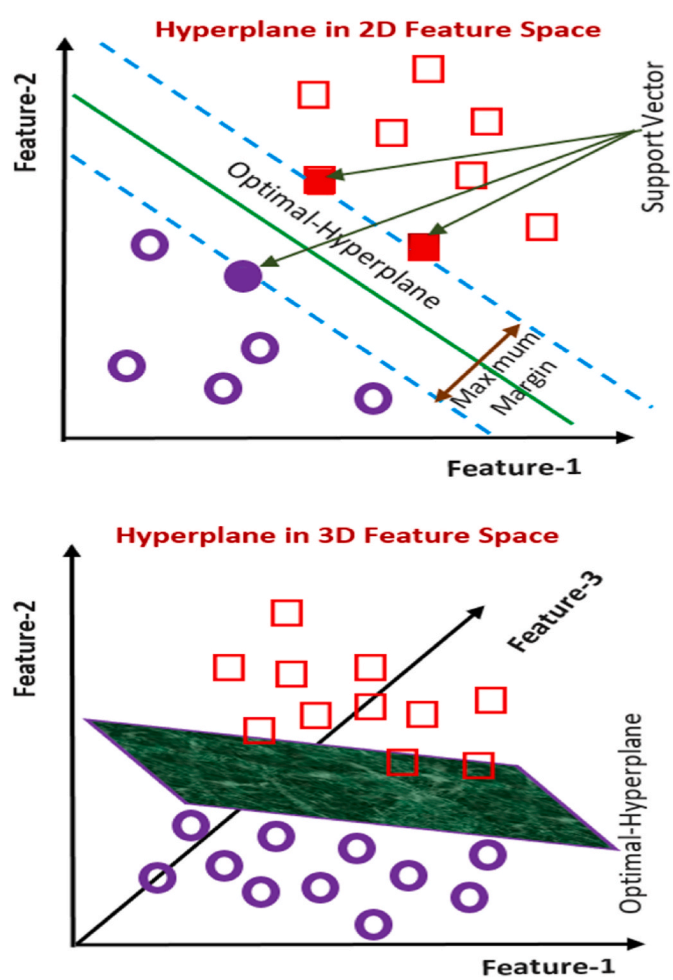

Fig. 13. Hyperplane in 2D & 3D feature space.

6.2.2. Convolutional neural networks (CNN)

CNN is a special class of deep neural network, which makes use of stacked architecture of various convolutional operations. These convolutional operations are result of joint contribution of convolutional layer, pooling layer, ReLU layer, fully connected layer & Softmax layer as depicted in Fig. 14.

CNN was designed mainly for handling high dimensional data like images or for computer vision task. Its architecture type is prevailing to identify objects available in image or video. Different layers present is CNN architecture have their different solo utility like convolutional layer to generate feature map of input image using different sized filters, also referred as kernels or in other sense it is somewhat relates to extraction of feature of target objects on image locally. Convolutional layer is subject to be ended with ReLU activation to allow non-linearity by replacing all negative values of pixel with zero. Pooling layer as next stacked element of CNN, is responsible for reducing the dimensionality of image given in input, resulting lower weights computation by network during backpropagation process.

All these layers extract necessary feature from image, which are than fed into fully connected (FC) layer with Softmax activation function. FC layer is responsible for prediction or classification of output labels. With a advantage of auto feature extraction form input images, CNN have some disadvantage i.e., large data is required to get fair amount of prediction accuracy, it don't encode the orientation & position of object, significantly slower because of pooling operation and lastly it is more sensitive to noise present in input data [46,54,69,80,96,104,113,125,130,142,156,161,169].

6.2.3. K-nearest neighbors (KNN)

KNN is another frequently used supervised machine-learning algorithm, which mostly used for prediction and classification task. It is a non-parametric kind of algorithm, as it does not require training phase explicitly for making any further generalization out of data points. The main aim of KNN is to classify or predict new or unseen data point based on similarity measure. Fig. 15 depicts the process of KNN, which includes selection of appropriate integer value of parameter "K" at first step, which refers to count of nearest neighbors to undertake for majority voting process. Second step is to compute the distance between all training data points and individual test data points. Various distance metrics are in vogue to calculate distances among different data points, however hamming or Manhattan, Euclidean and Murkowski distance metrics are most frequently used distance metrics during KNN implementation by various researchers. Third step includes sorting of calculated distances in ascending order, which is followed by last step of KNN, which is to choose top K instances from sorted list and to assign class label to individual test data point based on majority voted class labels observed in selected K instances in previous step.

Although higher interpretability of KNN results and high prediction efficiency with significantly less computation time makes it most frequently used algorithm, however it is been susceptible to quality & scale of the data as well as irrelevant features and its high memory requirement for storing all the training data make it computationally expansive, which may restrict its use case sometimes [56,70,74,85,117,122,137,145,150].

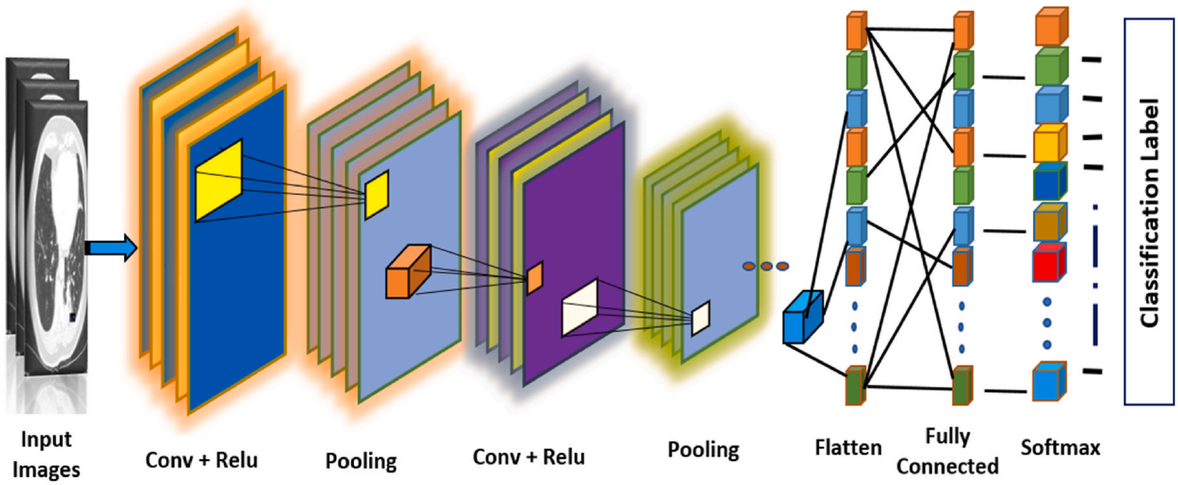

Fig. 14. CNN architecture.

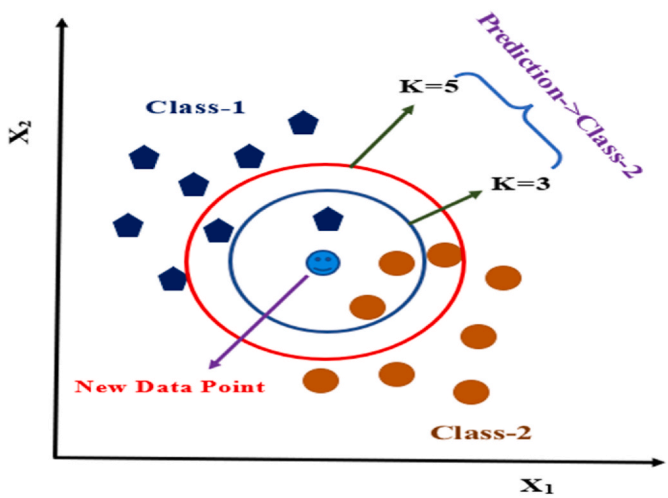

Fig. 15. Process flow of KNN.

6.2.4. Principal component analysis (PCA)

PCA is a popular dimensionality reduction technique in machine learning domain and typically used for reducing dimensionality of dataset containing high numbers of features or variables. Dimensionality reduction helps to make machine-learning algorithms less complex making it to overcome overfitting issues and able to sustain with improved generalizability and performance. The key aim of PCA-based feature extraction process is to create new group of independent features using stand-alone or combination of different existing features present in dataset while retaining only features, which are most important for predicting target feature, thus preserving significant representation of initial dataset even after transforming original features in independent principle components. PCA process begin with standardization of the range of initial features followed by computation of covariance matrix to unfold correlation among features. Next step is to calculate and arrange eigenvector & respective eigenvalues of covariance matrix in descending order, where eigenvector & respective eigenvalues apprehend the principal component and measure of variance respectively.

Last step is to select eigen-pairs with maximum eigenvalues from feature vector generated during previous step, representing first principle component that preserve the utmost information from the initial dataset. PCA enhance the performance of machine learning algorithms

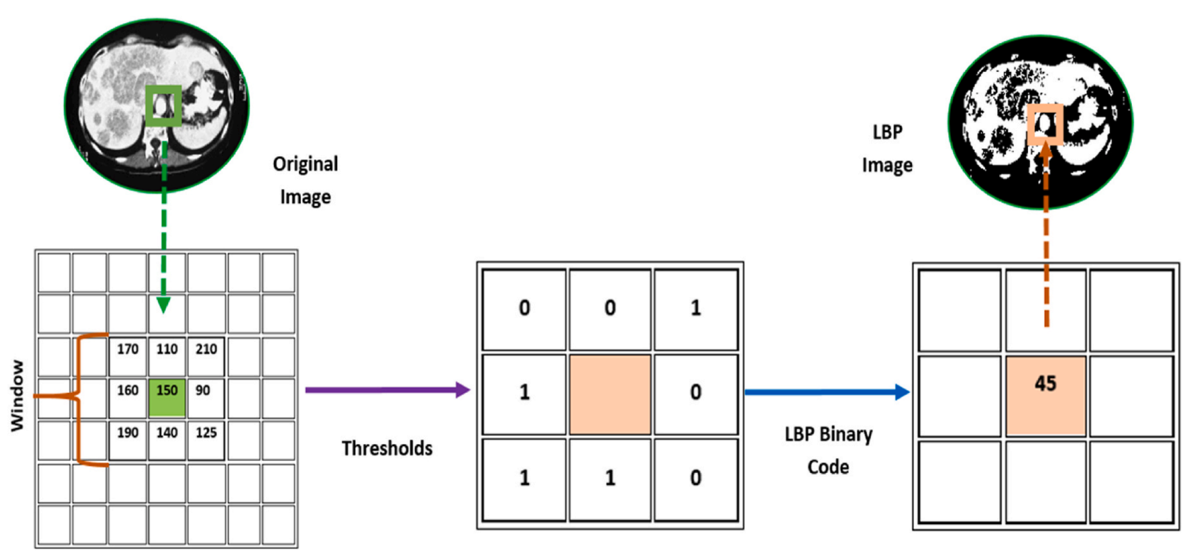

Fig. 16. Process flow of LBP.

by eliminating non-contributor feature from feature space. However it has some disadvantages i.e., PCA requires standardized data only to select adequate principal components, proper evaluation of covariance may seems difficult and transformation of actual features into linearly uncorrelated variables may led PCA to be tough to interpret or read with respect to actual feature [46,56,72,81,102,115,122,150].

6.2.5. Local binary patterns (LBP)

LBP, a simple & powerful feature extraction algorithm, is popular for its ability to identify important features by differentiating minute differences in topography & texture of images at significantly low cost of computation. Light fluctuations or variations in image's gray-scale values may not affect LBP algorithm's performance, making LBP suitable choice for real time applications i.e., texture segmentation, facial image recognition, image processing etc.

The aim of LBP is to generate feature vector of an image by encoding image's geometric features after detecting microstructures i.e., edges, spots, corners, hard lines and flat areas etc., in images using histogram estimations. Steps involved in LBP includes gray-scale conversion of image, image traversal of a window having predefined neighborhood value and label assignment of central pixel as depicted in Fig. 16. A threshold, according to association between center and adjacent pixel, is calculated and applied. Then, using obtained neighborhood values in anti-clockwise or clockwise direction, LBP matrix is computed mathematically, which serve as structural model of the textural structure present in image [57,75,102,127,134,139,164].

6.2.6. Histogram of oriented gradients (HOG)

HOG, a popular feature descriptor, typically used for feature extraction from an image and frequently used in image processing & computer vision domain. Finding shape & structure of physical entities present in image is the key focus of HOG. Unlike other edge detector methods like Canny Edge detector and SIFT, HOG counts incidences of gradient orientation in the localized area of an image and consider computing feature utilizing magnitude & gradient angle making it more powerful & better to be used for real time application.

As represented in Fig. 17, steps involved in HOG process flow includes resizing of image to a pre-specified image size, which make it suitable to extract tiny patches of image and led to less complex computation. Next step is to calculate gradient for each pixel by determining center pixel first followed by calculating differences in values of right & left pixel and above & below pixel of the center pixel, resulting gradient calculated in horizontal & vertical direction. Next step includes computing magnitude & orientation of each pixel value mathematically by utilizing calculated gradient in previous step and creating histogram using computed magnitude & orientation as well. Final step includes normalization of gradients from image's patches of 8 × 8 blocks to 16 × 16 blocks patches to reduce lighting variation available in image and generation of HOG features for complete image by combining all 16 × 16 patches together at once. HOG performs quite well in object detection, however it found to be highly sensitive to image rotation leaving it under cap of limited application in image processing domain [46,58,134,139,145,164].

6.2.7. Gray level co-occurrence matrix (GLCM)

GLCM is another popular texture feature descriptor alongside LBP, which typically represents pixel pair wise joint distribution probability or deals with inferring degree of correlation in pixel-pair of image using second order statistic. In the process of GLCM, two pairs of pixels need to be selected from different region of images like one pair for heavily textured area of images & another from clean or low textured area of image. After which GLCM generate degree of correlation between these pairs of pixels using statistic, where higher degree represents unavailability of texture in images and lower degree signifies presence of heavy texture in image. These computations are carried out multiple times for different distance & angles specifying various spatial relationship among pixel-pairs in image. GLCM forms a matrix representing probabilities of pixel-pair correlation and may be used to extract different statistical measures showing information about texture properties of an image i.e., correlation, contrast, dissimilarity, homogeneity, energy etc. Although GLCM is efficient feature descriptor to extract texture features from image, however it performs significantly well, only when its use case involve requirement of quantization of texture in an image [50,62,73,84,101,110,127,137,158].

6.3. Challenges in cancer diagnosis using ML/DL techniques

Emergence of ML/DL-based techniques have enriched cancer diagnosis area with its overwhelmed efficiency in computation of complex problem with lower error-rate than humans. A measurable revolution has been witnessed in the development of ML/DL-based – computer aided system for cancer detection during past decade. However, still there are various challenges associated with ML/DL-based cancer diagnosis. Some of observed challenges during this study are as follows:

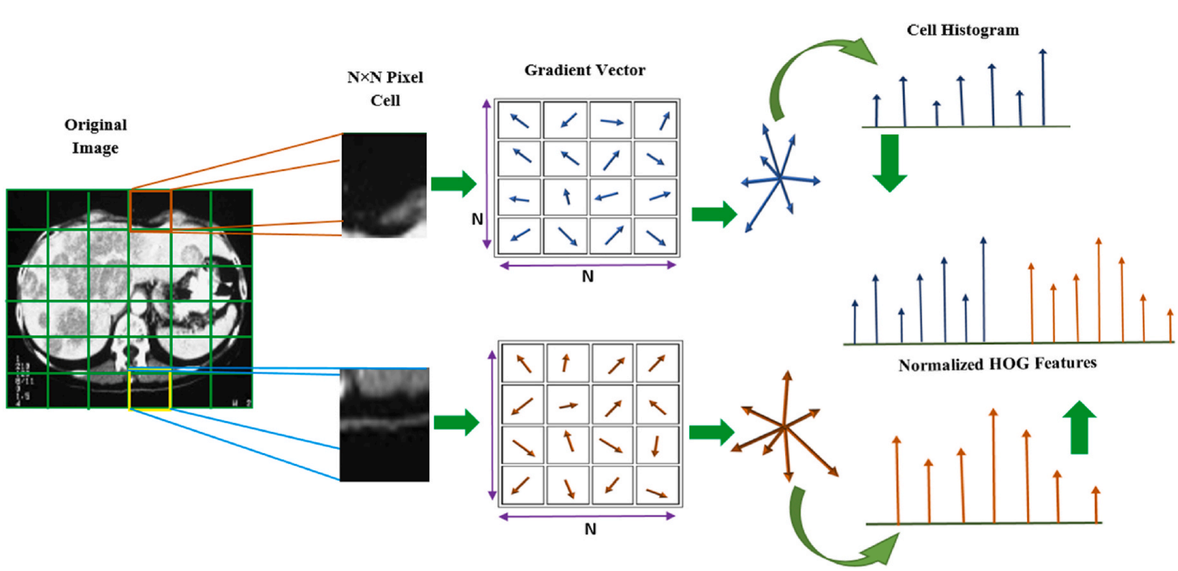

Fig. 17. Process flow of HOG.

- ML/DL-based methods require large amount of data samples for correct generalization of classification model. However, in the area of cancer diagnosis, availability and access of such large sized dataset may possibly not attainable most of the time due to privacy concerns of patients participated in dataset or due to data sharing policies of organizations holding that dataset. Government or regulating agency's intervention in such organization's data sharing policies may explore more alternatives for better advancement of predictive model's efficiency by employing appropriate provision for secure & privacy-preserved distribution of large sized dataset between researchers and such organizations.
- Apart from unavailability of large sized disease datasets required for AI-based model development, availability of limited number of completely labelled dataset is observe to be major challenge in cancer diagnosis task. Researcher had employed their ML/DL-based methods either on datasets where only limited number of samples were correctly labelled or they were dependent on expert's decision for validation of data labels, where researcher don't have labelled data in hand. In such cases, semi-supervised ML/DL methods may help researcher up-to some extent.
- Data imbalance is also a major concern at the time of cancer diagnosis using ML/DL methods as it is very difficult to obtain balanced datasets in medical domain. Balanced dataset refers to a dataset, which contains almost equal portion of instances of every class i.e., patient class & healthy class. Typically, this type of dataset may not possible to get due to the reason; institutions involved in testing or screening of patients do not bother to preserve data of healthy people. Imbalanced data, as input to ML/DL model may led to emergence of bias in prediction of employed model. Although statistical solution like oversampling & under sampling and data augmentation techniques may resolve this issue up to reasonable extent, however improper use of these methods may results to introduction of variance & bias in the data and further in poor prediction of model.
- Another challenge in cancer diagnosis using ML/DL methods is different variations available in input data. These variations may include different data modalities present in datasets like CT and MRI scans recorded for specific cancer type, same patient's scans captured by different institutional bodies or labs having different hardware & software, and data variations perceivable due to different lightning conditions used during data capturing. Apart from these, variations exhibits due to different data utilized at the time of model development & model deployment phase, remains key challenge in ML/DL based cancer diagnosis. Researchers generally develop their model using standard datasets openly available for research & social good purpose, which are usually in processed or standard formats required by ML/DL algorithms. However, real time applications of such models may not possible as real time raw data may not follow standard format and may need preprocessing before passing it to developed model.
- Efficient feature extraction & feature selection is the backbone of optimized ML/DL model development as it minimize misclassification by ML/DL-based methods thus improving classification accuracy. Feature extraction & feature selection refers to identification as well as extraction of most impactful, useable & highly correlated features from raw data available in hand. Although researchers utilized various methods for extraction of different statistical, texture, morphological & deep features from medical data in the recent past, but position of some organ i.e., pancreas, in human body may adulterate the quality of extracted feature vector and may results into increased misclassification by ML/DL model. Apart from this, at the higher cost of computational complexity, combination of multiple type of features may utilize for obtaining optimized classification accuracy by ML/DL model.
- Researchers typically develop their ML/DL-based predictive model for specific type of data modality. Which may not generalize well on other modality type and may increase misclassification rate of predictive model thus results into low accuracy. Robustness and accuracy of a predictive model may enhance, if researchers try to develop their predictive model for cancer diagnosis using multiple types of data modalities. However, probability of procuring such multi-modality data of cancer patients seems to be difficult due to either unavailability or less availability of such data. Apart from this, inclusion of multiple types of input i.e, medical images, clinical parameters, physical examination remarks & genetic data as input to ML/DL model, may also enhance diagnostic ability of developed predictive model.
- Computational complexity of a predictive model is another challenge a researcher may face during development of their ML/DL model. Very few of researchers, tried to bother about time & space complexity of developed ML/DL model in the past. However, computational complexity measures of predictive models are in vogue now a day. Therefore, researchers need to develop predictive model, having higher classification accuracy withstanding low computational complexity during development as well as evaluation of ML/DL-based predictive model.
- Concept of transfer learning seems very useful in the cancer diagnosis scenario where procurement of large-scale datasets found to be difficult or almost impossible due to privacy concern of patients. Due to small scale dataset in hand to work upon, various researchers already made use of transfer learning during cancer diagnosis using pre-trained models in recent past. However, prime concern of using pre-trained models is higher probability of misclassification by predictive model as most of these pre-trained models were either trained or evaluated on non-medical datasets. Therefore, it is need of hour to develop and provide more pre-trained model for social good, which are specifically trained or evaluated on large-scale medical datasets only.
- Presence of noise, variation in lesion's size, irregular shape or fuzzy boundaries of cancer lesion are further important matters of concern during cancer diagnosis using medical image modality. As these facts may increase image's complexity making it difficult to interpret and tough to locate lesion location, thus resulting to higher probability of misclassification of developed ML/DL model. Hence, greater care needs to be adhered at pre-processing phase of predictive model's development to cop up with such type of issues present in image modality.
- Although ML/DL-based methods have shown their promising predictive capability in cancer diagnosis domain so far, yet these solutions are still far from public acceptance due to black-box nature or un-explainability of results obtained from utilized ML/DL methods. Various researchers already used various ML/DL methods to diagnose different cancer types using different explainability frameworks i.e., local interpretable model-agnostic explanations (Lime), SHapley Additive exPlanations (SHAP) and partial dependence plots (PDP), thus resulting public acceptance of applied ML/DL methods. Research on explainability of deployed models is still in its early phase and is still unable to gain public acceptance, hence it remains a challenge to current researchers to make their developed ML/DL model more explainable to the public to be clinically acceptable in cancer diagnosis area.

7. Conclusion

A measurable revolution has been witnessed in the development of machine learning and deep learning -based computer aided system for cancer detection during past decade. Many of the researcher either had contributed or are going to present their work in the field of cancer diagnosis, using AI or machine learning methods in near future. Therefore anyone, who is willing to work in the area of cancer diagnosis through AI-based methods, needs to go through previous studies on it & may seeks summarized survey or review study on the same. Keeping in mind the above said motive, this review paper has presented systematic analysis of utilized, in-vogue ML/DL-based methods for detection & diagnosis of six cancers types i.e., lung, breast, liver, brain, pancreas and skin cancer. Analysis, review and categorization of different ML/DL-based methodologies for six cancer types detection, along with different feature extraction techniques, were the key emphasis of this study for past six years from 2016 to 2021. Furthermore, this review has explored four particular stages of computer assistive cancer diagnosis i.e., image pre-processing, segmentation, feature-extraction & classification using standard benchmark datasets.

Although, observed accuracy of utilized ML/DL-based methodologies signified lower error rate than humans, still it is far from real world use cases as one can't belief on result provided by AI methods. One of the reasons could be un-explainability of interpreted results by used ML/DL model & other could be that most of the researchers either applied these methodologies on small dataset or did not employ benchmark datasets. For this purpose, the recent state-of-art methods are analysed on benchmark datasets and limitations of existing techniques are highlighted. Main research challenges observed in this study in the area of cancer detection using ML/DL methods includes scarcity of domain knowledge due to busy schedule of clinician or radiologist, unavailability of large scale public dataset due to privacy concerns of patients, imbalanced & un-labelled dataset, unobtainability of standardised ML/DL pipeline, lack of efficient & innovative feature engineering method to further enhance accuracy of current state-of-art methods and last but not the least is black box characteristic of ML/DL-methods utilized during classification of various cancer types. Systematic summarization of different facts i.e., methodology, feature extraction techniques, dataset utilized, modality used & accuracy received, from recent six years on six cancer type detection using ML/DL methods makes this review study, suitable for new researcher's use, who are going to contribute in this domain for social good in future.

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Declaration of competing interest

All authors declare that there is no conflict of interest in this work.

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