JOIV : Int. J. Inform. Visualization, 8(3-2): IT for Global Goals: Building a Sustainable Tomorrow - November 2024 1590-1598

INTERNATIONAL JOURNAL
ON INFORMATICS VISUALIZATION

journal homepage : www.joiv.org/index.php/joiv

A Comprehensive Review on Cancer Detection and Classification Using Medical Images by Machine Learning and Deep Learning Models

Jayapradha J [a,b], Su-Cheng Haw [b,*], Palanichamy Naveen [b], Elham Anaam [b]

[a] *Department of Computing Technologies, School of Computing, SRM Institute of Science and Technology, Kattankulathur, India*
[b] *Faculty of Computing and Informatics, Multimedia University, Cyberjaya, Selangor, Malaysia*
*Corresponding author: *sucheng@mmu.edu.my*

***Abstract*—In day-to-day life, machine learning and deep learning plays a vital role in healthcare applications to predict various diseases such as cancer, heart attack, mental problem, Parkinson, etc. Among these diseases, cancer is the life-threatening disease that leads a human being to death. The primary aim of this study is to provide a quick overview of various cancers and provides a comprehensive overview of machine learning and deep learning techniques in the detection and classification of several types of cancers. The significance of machine learning and deep learning in detecting various cancers using medical images were concentrated in this study. It also discusses various machine learning and deep learning algorithms that lead to accurate classification of medical images, early diagnosis, and immediate treatment for the patients and explores the methodologies which has been used to predict the cancer with the help of low dose computer tomography to reduce cancer related deaths. As the study narrows down the research into lung cancer, it combats the findings limitations in lung cancer detection models and highlights the need for a deep study of novel cancer detection algorithms. In addition, the review also finds the role of setting up data in lung cancer and the potential of genetic markers in stabilizing the accuracy of machine learning models. Overall, this study gives valuable suggestions to achieve more accuracy in cancer detection and classification using machine learning and deep learning techniques.**

***Keywords*—Machine learning; deep learning; healthcare; cancer; medical images; lung cancer.**

Manuscript received 11 Jul. 2024; revised 2 Sep. 2024; accepted 23 Oct. 2024. Date of publication 30 Nov. 2024.

I. INTRODUCTION

Cancer has grown to be a serious public health concern and a silent killer of millions of people worldwide. It was determined that 14,61,427 cancer cases occurred in India in 2022. In India, around one in nine individuals will encounter cancer at some point in their lives[1]. With an expected ten million deaths in 2020, cancer was ranked as the second largest mortality rate in the World Health Organization's survey report [2] and more than 100 kinds of cancer according to its characteristics. The most common categories of cancer are (1) Bladder cancer, (2) Breast Cancer, (3) Colorectal Cancer, (4) Kidney Cancer, (5) Lung Cancer, (6) Lymphoma, (7) Pancreatic Cancer, (8) Prostate Cancer, (9) Skin cancer and (10) Uterine cancer[3]. Fig. 1 depicts the number of persons pretentious by diverse cancer categories as per the facts.

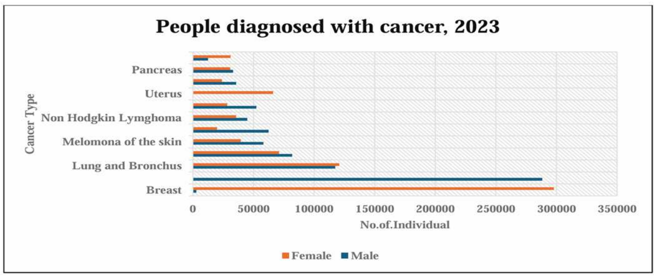

Fig. 1 Number of persons pretentious by diverse cancer categories

The number of American deaths from cancer is predicted to be 609,820 in 2023. There are 127,070 predicted deaths from lung and bronchus cancer, making it the disease with the highest death toll in US. Fig. 2 displays the original cancer cases and cancer demises in 2023[4].

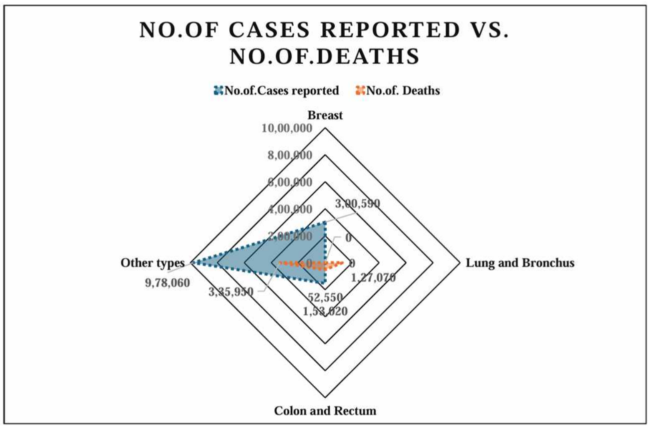

Fig. 2 Number of new cancer cases and cancer deaths in 2023

Our study is going to have a detailed erudition of five cancers such as (1) Breast cancer, (2) Brain tumor, (3) Cervical cancer (4) Skin cancer and (5) lung cancer. As our research is going to concentrate on the most prevalent cancer called "Lung Cancer", more detailed studies about lung cancer are done in this study. In the US in 2023, there were 2,38,240 cases reported of lung cancer and 1,27,070 deaths due to lung cancer. To test the abnormalities in the lungs, various tests such as Computed Tomography and mammography have been conducted. The captured images are analyzed using recent technologies such as Computed Tomography (CT)[5], Neural Networks, Machine Learning (ML)[6], and Deep Learning (DL)[7] for the classification of different cancers.

Traditional methods of lung cancer categorization use a visual assessment of imaging studies with radiologists using criteria relating to tumor features such as extent, figure, and position to determine the cancer type and stage. However, such procedures are susceptible to subjective bias and may result in variations in interpretations between observers. In response to these problems, machine learning algorithms have emerged, aided by improvements in artificial intelligence (AI), to systematize the interpretation of medical imaging for lung cancer uncovering. These AI-powered technologies provide a more uniform and rigorous approach to classification, improving the accuracy and reliability of lung cancer diagnosis. The following points emphasize the benefits provided by AI in this context: (1) AI systems provide consistent picture analysis, decreasing the subjective turbulence associated with human interpretation, (2) Accurately classify medical images by detecting minute features and patterns that humans may overlook, (3) Automated systems evaluate large volumes of data quickly, which results in faster diagnosis and treatment. (4) Machine learning models improve with more information, resulting in more accurate classifications, (5) AI can help anticipate treatment outcomes, leading to more individualized patient care, and (6) Methods may help researchers uncover unusual imaging variables and understand complex biological interactions in cancer. Thus, using AI in lung cancer classification is a significant step forward, providing more objective, precise, and efficient diagnostic capabilities. Such developments help medical professionals make more educated treatment decisions, leading to better results for patients with lung cancer [8]. Numerous research has been undertaken on lung cancer, with a focus on the different models used for early diagnosis. However, a more in-depth review of these studies demonstrates numerous research gaps.

- This study examines the current state of cancer detection models, which serve as essential for researchers and presents an overview of the various cancer detection methods presently in use.
- This study analyzes the cancer detection algorithms such that the pros and cons of the algorithms can be understood before integrating them into current frameworks and concentrating on the lung cancer detection model as a priority. As a result, this review study is unbelievably valuable for researchers working on various cancer detection models.

The paper is organized as below: Section II discusses materials and methods that reviews the detection and classification using ML and DL in health care and explain five cancers such as (1) Breast Cancer, (2) Skin Cancer, (3) Brain Tumor, (4) Cervical Cancer, and (5) Lung Cancer. Section III describes results and discussions that cover the limitations in existing systems and discussions. Finally, section IV concludes the study with a conclusion.

II. MATERIALS AND METHOD

A. Detection and Classification Using Machine Learning and Deep Learning in Health Care

ML includes various types of models and algorithms to bring out solutions for various problems [9]. Many of the machine learning models are not multi-layered; thus, the image preprocessing and the data segmentations are done before feeding into the models[10]. As multi-layered algorithms are not widely available, the procedure of data pre-processing is becoming hectic to make the perfect predictions and to eradicate the over and underfitting of the prepared dataset. DL is one the main forms of ML that employs multi-layered neural networks to increase accurate prediction where the multi-layered networks can learn by themselves, recognize, and comprehend from data [11]. Machine learning has wide applications in healthcare such as (1) Electronic Health care [12], (2) Geonomics [13], and (3) Data Imaging [14]. Medical imaging has contributed much to the advancement of machine learning algorithms using various types of imaging modalities such as CT, magnetic resonance imaging (MRI), x-ray, positron emission tomography (PET), ultrasound, and others. The above-mentioned images are input to various models to detect cancers [15], injuries[16], and fractures [17]. Various cancer and the models implemented using DL and ML are discussed as follows.

B. Breast Cancer Analysis Using DL and ML Methods

Compared to the traditional methods, DL and Artificial Intelligence techniques are more effective for the identification of cancers. An artificial intelligence system was implemented to beat the manual prediction of breast cancer by the radiologist through AUC-ROC by 11.5% in the US and the UK datasets [18]. A unique computational model is proposed by associating various ML algorithms such as Monte Carlo feature selection, Random Forest, and rule-based to detect the breast cancer genetic factor [19]. In[20], breast cancer classification is done by two algorithms such as (1) Naive Bayes (NB) and (2) K-nearest neighbor (KNN) and the (3) KNN model is found to be with accuracy of 97.51%. Three ML algorithms such as C4.5, Artificial neural network, and support vector machine have been implemented on the Iranian dataset and the performance of the algorithms is measured for sensitivity, specificity, and accuracy. Out of three algorithms, the support vector machine has the highest accuracy of 95.7% [21]. Two models such as Naïve Bayes and K-Nearest Neighbor have been implemented to classify breast cancer and the results are compared and proved that KNN has the highest performance compared to the Naive Bayes [22]. In [23] the study has explored that the deep learning techniques perform better as the DL algorithms can easily distinguish between the normal and cancer cells due to the various layers and proved that multilayer perceptron has good efficiency in examining the breast cancer.

The examination of the tumor is executed by examining the four biomarkers to predict breast cancer. Two approaches such as stratified and k fold cross validation were used to find the accuracy of the model and validating the neural network[24]. The artificial neural networks algorithm has been used to detect the nodes in the breast and to predict breast cancer. Four biomarkers were fixed for the prediction of breast cancer and 2-fold cross-validation has been used and achieved ~63% accuracy.[25] Automatic cancer detection was implemented on the MIAS dataset and the deep learning methods such as (1) Sars Autoencoder, (2) Stacker Sparse Autoencoder and (3) convolutional Neural Network have been implemented. Out of three, the Stacker Sparse Autoencoder has performed better with 98.9% [26]. Table I presents the various accurate predictions on breast cancer.

TABLE I
VARIOUS PREDICTIONS OF BREAST CANCER

References	Accuracy
Sana et al. [27]	97.53%
Dina et al. [28]	87.20%
Mohd et al. [29]	90%
Raquel et al. [30]	97%
Ragab et al. [31]	96.92%
Kavitha et al. [32]	98.50%

C. Skin Cancer Analysis Using DL and ML Methods

There are six types of skin cancer such as (1) Basal cell Carcinoma (BCC), (2) Squamous cell carcinoma (SCC), (3) Melanoma, (4) Bowen's Disease, (5) Keratoacanthoma and (6) Actinic Keratosis (AK). Most of the people pretentious by skin cancer are exaggerated by the Melanoma type of cancer and thus 75-80% of the people are affected by Melanoma cancer. ML techniques have been used to detect skin cancer. The main objective is to classify skin cancer as Melanoma, normal skin, and abnormal skin.

Recently, the 2032 skin disease imageries were categorized using a Convolutional Neural network (CNN). CNN has shown great potential in classifying skin cancer images. CNN is trained with larger scale of datasets to test its performance against 21 boarding-certified skin doctors on surgery-established scientific imageries with two grave binary classification use circumstances: (1) keratinocyte carcinomas versus benign seborrheic keratoses; and (2) malignant melanomas versus benign nevi [33]. Four ML methods such as K Nearest Neighbor, Support Vector Machine, Decision Tree and ANN were used to identify skin cancer. The above methods were compared for their accuracies and proved that ANN had the best performance and accuracy [34]. The collective output of various layers of the deep convolutional neural network to classify the images with high accuracy has been performed and the four-layer output of the deep neural network is amalgamated to get outstanding accuracy [35].

Deep Learning Convolutional Neural Network (DLCNN) has been used on the ISIC dataset to stratify extricated features for melanoma classification. During the implementation of DLCNN, followed by segmentation, the cancerous cells are extracted and classify whether the cells are benign or malignant [36]. In [37], the author proposed an Elevated level of intuition for the discovery of cancerous skin regions. Particle Swam Optimization along with Support Vector Machine (SVM) were used for optimization and grey level co-variance matrix (GLCM) has been implemented to extract the skin cancerous region. GLCM and SVM were implemented and attained 94% and 95% of accuracies respectively. Table II presents the various accurate predictions on skin cancer.

TABLE II
VARIOUS PREDICTIONS OF SKIN CANCER

References	Accuracy
Rasmiranjan et al. [38]	93%
Togacar et al. [39]	95.27%
Ebrahim et al. [40]	84%
Tumpa et al. [41]	97.7%
Dezhong et al. [42]	87.5%
Farhat et al. [43]	95.4%

C. Cervical cancer Analysis Using DL and ML Methods

Cervical cancer is a foremost topic among the millions of women in the world and the late detection of cervical cancer leads to danger. Earlier, cervical cancer was diagnosed using a pathological test which leads to very low accuracy of detection. Previously traditional methods such as SVM, Logistic regression, and Random Forest were used. As the ML zone increased models such as CNN and various DL classifiers methods were used for the identification of cervical cancer. An SVM-based classifier was used in the study to detect cervical cancer and obtained 98% accuracy[44]. A super pixel and CNN grounded segmentation is proposed for the detection of cervical cancer cells and a CNN-based segmentation is applied using deep learning methods and achieves an accuracy of 94.5% [45]. The study addressed the restriction of existing methods by suggesting a method to categorize cervical cancerous cells based on deep features using CNN. CNN-based feature extraction is implemented for classifying the cervical cancerous cells and achieved an accuracy of 98.3%.[46]. An analysis method has been proposed to examine the cervical cancer cell and segmentation of image is also performed to extract the various features for diagnosing cervical cancer. Various SVM classifiers are used to examine cervical cancer cell and achieved the accuracy of 98.5%[47]. A new deep learning model was developed by the combination of GLCM, Gabor filter, SVM and CNN. The above model has achieved a strong feature extraction of the cervical cancerous cells. The CNN model has been implemented with an extreme learning (EL) classifier and along with the EL, various classifiers were also scrutinized and obtained an accuracy of 91.2% [48]. The author compared two deep learning models such as (1) Hybrid deep feature fusion and (2) Late fusion and concluded that the Hybrid deep feature fusion has greater classification than the Late Fusion. The proposed model also has implemented deep learning with 7- 7-class classification and achieved higher accuracy at the level of 2- 2-class classification[49]. Table III presents the various predictions on cervical cancer.

TABLE III
VARIOUS PREDICTIONS OF CERVICAL CANCER

References	Accuracy
Vaiyapuri et al. [50]	99.6%
Ershad et al. [51]	98.8%
Naif et al. [52]	99%
Jiayi et al. [53]	83.16%
Gaurav et al. [54]	94.94%

D. Brain Tumor Analysis Using DL and ML Methods

Brain tumors are triggered by the unwanted development of cells in the brain which needs early attention. The main challenge in the recognition of brain tumors is identifying whether the tumor is present or not due to the multifaceted structure, shapes, and intensities of the brain. Segmentation of the brain image is a bit challenging as the grouping of the same type of feature will lead to complexity. The region-based segmentation of the brain plays a major role in extracting the features of the brain. Various thresholding approaches and image processing methods are used for the detection of Brain tumors in MRI scan images. As a concern with the brain tumor, the MRI scan is better suited than the CT scan and X-ray. In [55], ML methods are implemented in a three-step process such as (1) Preprocessing, (2) Feature extraction using GLCM and (3) Classification. SVM classifier is also applied on the MRI brain images and the features are classified based on the shape, texture, color and achieved an accuracy of 97.1%. The study has concentrated on the de-noising technique, extraction of GLCM features, and segmentation of the brain tumor region. After the identification of the tumor, the morphological filters are used for de-noising. Later, PNN was used to classify brain tumors [56]. Though the feature extraction and classification of the brain tumor is more important, the preprocessing of the images is more important as it increases the quality of the images for classification. A study has implemented a Weiner filter with various wavelet bands to reduce the noise and increase the inputs. After preprocessing, the classification is performed using Local binary patterns and Gabor Wavelet Transform to achieve good precision and dice score [57]. Artificial Neural network (ANN) is executed in the MRI scan images by pre- and post-processing of the images followed by the feature extraction using mean and spatial gray level methods. The classification of the image's using ANN has achieved an accuracy of 99% [58]. Table IV presents the various predictions on Brain Tumor.

TABLE IV
VARIOUS PREDICTIONS OF BRAIN TUMOR

References	Accuracy
Khairandish et al. [59]	98.4%
Raheleh et al. [60]	95%
Milica et al. [61]	96.56%
Rajat et al. [62], [63]	99.04%
Yaswanth et al. [63]	96.44%

E. Lung Cancer Analysis Using DL and ML Methods

Medical imaging methods such as MRI and CT scans have become crucial for classifying and diagnosing lung cancer. CT and MRI are the most often used modes to acquire medical images, each having its own set of characteristics and clinical uses. CT scanning uses X-rays to create pictures of the inside components of the body and is especially effective at detecting chest abnormalities like lung cancer or pneumonia. The patient should be situated in such a way that the CT scan rays can penetrate the body. As the X-ray perceives the body, it detects the various functions of the body. The perceived rays will be examined by the computer and produce cross-section images. When compared to other imaging, CT imaging is a quick and easy process, and it requires a very minimal amount of time for processing. CT scans also provide substantially comprehensive images to doctors for the proper diagnosis of various diseases. However, the CT scan consists of ionizing radiation that could cause cancer if it is frequently repeated. The CT scans can be captured only if there is proper radiation protection. Moreover, the chances of positive findings are high in CT scan images as the patterns can also be identified as irregularities.

Several diseases can be diagnosed using CAD methods and the CAD methods forecast the seriousness of the sicknesses. The CAD methods play a major role in identifying the nodules in the lung CT scan. As the CT scan can only identify the bigger nodules, the CAD methods can be able to identify the smaller size nodules. In contrast, MRI generates pictures using radio waves with an intense magnetic field. This technique is particularly important since it can provide high-quality images without the use of ionizing radiation, making it excellent for imaging soft tissues such as joints, the spinal cord, and the brain.

Recently the impact of lung cancer has been huge and thus the need for early detection is vital. This study analyzes the various models used to diagnose lung cancer, which is one of the main causes of cancer-related death worldwide. Early and accurate detection of lung cancer is critical to increase patient survival rates and treatment success. Despite major advances in medical imaging technology, interpreting medical images remains a big issue, demanding sophisticated optimization models to improve diagnosis accuracy. The objective of this study is to compile and scrutinize current state-of-the-art optimization models and approaches used to diagnose lung cancer and to understand the ideas underpinning the models and their performance measures. By doing so, best practices, gaps in the literature, and potential areas for future research and development are discovered [64], [65].

F. Discussions on Dataset Accessibility for Lung Cancer Identification

CT is the maximum effective and best imaging mode for the detection of lung cancer. Thus, the first step in the detection of lung cancer is to get the lung CT images of the patients to detect the cancer in the preliminary stages. Getting the CT scan image datasets from the private and local hospitals has lots of procedures, thus various public datasets have been published widely for the usage of various experiments. Many lung cancer CT image datasets are available and among them, the most popular used dataset is below:

- Lung Image Database Consortium (LIDC), Lung Image Database Consortium and Image Resource Initiative (LIDC–IDRI) [66].
- Early Lung Cancer Action Program (ELCAP) [67].
- Nederland-Leuvens Longkanker Onderzoek (NELSON) [68], [69]
- Automatic Nodule Detection 2009 (ANODE09) [70]
- Lung Nodule Analysis 2016 (LUNA16) [71] and
- Database of Japanese Society of Radiological Technology (JSRT) [72].

TABLE V
A LITERATURE REVIEW OF THE LUNG CANCER DETECTION MODELS

No	Ref	Highlights
1.	Matthijs et al. [73]	Concentrated on the existing evidence for LDCT-based lung cancer screening and its therapeutic uses in high-risk groups globally. Addressed the effectiveness of costs.
2.	LG et al. [74]	Reviewed various CAD techniques that share the common objective of enhancing the role of radiologists in the detection of lung nodules. Highlighted deep learning systems results in impressive performance.
3.	Yi et al. [75]	Hereditary diagnosis of lung cancer, specific mutations are analyzed for the detection of lung cancer.
4.	Reem et al [76]	Focused on the biomarkers test that could lead to quick results of early analysis of lung cancer are analyzed.
5.	Muntasir et al. [77]	Implemented the ensemble methods and ML methods for the detection of lung cancer.
6.	Charles et al. [78]	Concentrated on small lung cancer and analyzed that the change in chromosome structure is the main cause of small lung cancer cells. The change in the structure is due to the degradation of function TP53 and RB1 genes. Thus, the control of the above genes is studied.
7.	Adiraju et al. [79]	Reviewed the study that concentrated on the detection of lung nodules and their classification.
8.	Dakhaz et al [80]	Support vector machine (SVM) classification is analyzed. Evaluation against various ML algorithms for lung cancer detection is studied and proved that SVM is the best.
9.	Iakovos et al. [81]	Analyzed the available risk prediction models and how they can be applied in lung cancer screening. The advantages and limitations of the existing models are discussed.
10.	Amrita et al.[82]	Examination of lung nodules through deep learning is presented. Various works using deep learning for lung cancer detection are presented.

Most of the experiments for the detection of lung cancer were conducted in the above datasets. Earlier the Lung Image Database Consortium had fewer images and later it was expanded to the Lung Image Database Consortium and Image Resource Initiative which has 1018 scan images associated with an XML file related to it. Radiologists examined the LIDC–IDRI dataset and categorized the images as having three types of lesions such as (1) Lung nodules less than 3mm, (2) Lung nodules greater than or equal to 3mm and (3) Lung Non-nodules greater than or equal to 3mm. The dataset LUNA 16 is part of the LIDC–IDRI dataset and the ELCAP database is made in association with the Vision and Image Analysis database. The main motive for publishing the NELSON dataset is to measure the lung nodule and to detect the lung nodule and its segmentation. The ANODE09 dataset comes from the NELSON dataset and the JSRT also consists of various lung nodule images to assess and measure the lung nodules. However, Table V has presented the in-depth literature survey of lung cancer detection, it is noticeably clear that the survey is not enough to give the needed knowledge on the best-suited models and techniques for Lung cancer detection. Thus, our review turns out to bring out the research gap in the models of lung cancer detection using lung nodule classification.

G. Role of Sequencing Data in Lung Cancer Diagnosis

Although the high-risk patients need to experience the various medical image testing to identify the stages of cancer, there are lot of cases had happened which leads to false diagnosis of cancer and its stages. The necessity of approaches for early lung cancer detection is very important. Thus, new advanced approaches need to be put in practice for the detection of lung cancer [83]. To overcome the necessity of new approaches, sequencing technology makes it possible to make use of various new methodologies for early lung cancer detection. During waiting time, the accurate classification of the lung cancer methodology is much needed. As a known fact, cancerous cells display an extensive variety of genetic versions and putting together all these versions could identify the mutational sequences in various types of cancer [84] [85].Due to the above reasons, the existing research has started concentrating on the genetic markers which can be the input feature to improve the accuracy of the machine learning models. In various studies, blood-based biopsies that use liquid are effective methodologies for early diagnosis of lung cancer. The examination of possible cancer markers makes use of exosomes, methylation, circulating tumor cells (CTCs), microRNA (miRNA), cell-free DNA (cfDNA) fragments, circulating tumor DNA (ctDNA), and methylation to identify the possible partying tumor indicators.

Cell-free DNA (cfDNA) fragments [86], circulating tumor DNA (ctDNA), microRNA (miRNA), methylation, exosomes, and circulating tumor cells (CTCs) have been identified to be effective approaches for examining possible tumors. The signals from the liquid biopsy are collectively combined with various judicial models to diagnose the tumors accurately with a great recognition degree. Single nucleotide variations are genetic changes that may frequently exhibit different characteristics in various types of lung cancer [87]. Thus, various studies have used genetic changes as the input to create systems to distinguish between the LUAD and LUSC [88]. Diverse changes, in particular, key promoters can change the number of genes to affect the cell function and abnormalities in cell-to-cell communications systems and thus different cancer is formed [89]. ML models help to identify the severity of the cancer by classifying the various patterns of cancer using RNA sequencing Data. A recurrent hidden Markov model shows excellent accuracy in classifying large genomic areas [90]. Patterns of methylation are used as a pattern to differentiate between early and malignant lung cancer [91]. Using the genes directly as the input characteristics, it possesses the risk of overfitting [92].

III. RESULTS AND DISCUSSION

A. Limitations in existing models

Before feeding datasets to the machine learning models, and analyzing them using CT scans, a lot of things need to be dealt with while applying it to the diverse datasets. Such restrictions affect the accuracy and the dependency of the various classification processes. A few limitations are listed as follows:

a. Challenges arise in the preprocessing due to the uncertainty required for effective management to give the best output.
b. Quality of the equipment and changes in the imaging processes decide the quality of the images, image sections, brightness and the noises present in the scan images.
c. Due to technical errors such as mobility and hardening the image quality may be affected and thus the irregularities in the images might make the pre-processing difficult.
d. Due to the irregularities, detecting and identifying the segmentation of the features are very crucial.
e. Not-diversified data may lead to poor performance results and thus the machine learning models may not give the best results.
f. Precise annotation of the CT scan images is challenging and laborious when the complex segmentation task is involved in the labelled data whereas the unlabeled data would act as a hindrance to achieving better results in the machine learning models.
g. Using different datasets results in bias and contradictions in the training process.
h. The management of needed data is very crucial while the demand for processing is reduced during the data augmentation, normalization and scaling.
i. Due to improper data pre-processing methodologies, the performance of the entire system may be decreased, and data loss might happen.
j. Most of the existing studies involving cancer detection lack diversified images methods for identifying and detecting cancer.

To address all the concerns, effective algorithms methods and participating in collaborative efforts across various institutions and collecting diversified datasets is essential.

B. Discussions and Directions

Preparing the ML and DL models before applying to various CT images for the detection of cancer faces several challenges. The primary challenge is due to datasets and their sizes. The few challenges are discussed below:

1) Importance of Artificial intelligence in healthcare: Investigate by considering the benefits and limitations of various machine learning and deep learning algorithms used in cancer detection.

2) Exploring the various medical imaging data set: Medical data sets play a major role in various cancer prediction and classification. This helps physicians for accurate diagnosis and early treatment of various types of cancer. In recent days, AI models have proved that it is more effective in analyzing and interpreting these medical data sets.

3) Detection of cancer in early stage: To improve the treatment for cancer, early detection by AI models plays a significant role in the medical field.

4) Genetic markers roles: By integrating the genetic data with medical imaging dataset, overall performance of the cancer prediction models can be enhanced.

5) Obstacles and Restriction: While developing lung cancer prediction models using machine learning and deep learning algorithms, several obstacles and limitation may occur. By addressing these issues, the researcher may get clear ideas to narrow down their works.

6) Clinical incorporation: Conversation around the openings and issues of using machine learning and profound learning models in clinical settings to analyze cancer, taking into consideration things like integration with current healthcare frameworks, moral issues, and administrative endorsement.

IV. CONCLUSION

Finally, this study integrates machine learning and deep learning in cancer detection and classification. By taking advantage of the power of machine learning and deep learning techniques, healthcare experts can achieve greater accuracy in diagnosing and treating cancers. Many research and inventions in cancer detection are essential for realizing the technologies in clinical practice. This article addresses the limitations such as equipment quality, imaging process and data diversity are crucial for enhancing the accuracy and effectiveness of deep learning models in lung cancer detection from CT scan images. In future robust data preprocessing techniques can be identified to improve the accuracy in lung cancer detection which can lead to prevention of human deaths in this world.

REFERENCES

[1] J. A. Bachman, B. M. Gyori, and P. K. Sorger, "Automated assembly of molecular mechanisms at scale from text mining and curated databases," Molecular Systems Biology, vol. 19, no. 5, Mar. 2023, doi:10.15252/msb.202211325.

[2] P. Jurmeister et al., "Machine learning analysis of DNA methylation profiles distinguishes primary lung squamous cell carcinomas from head and neck metastases," Science Translational Medicine, vol. 11, no. 509, Sep. 2019, doi: 10.1126/scitranslmed.aaw8513.

[3] A. E. Sloan et al., "ABTC-0904: targeting glioma stem cells in GBM: a phase 0/II study of hedgehog pathway inhibitor GDC-0449," Journal of Neuro-Oncology, vol. 161, no. 1, pp. 33–43, Dec. 2022, doi:10.1007/s11060-022-04193-3.

[4] B. A. et al, Molecular biology of the cell . 2022.

[5] F. Alharbi and A. Vakanski, "Machine Learning Methods for Cancer Classification Using Gene Expression Data: A Review," Bioengineering, vol. 10, no. 2, p. 173, Jan. 2023, doi: 10.3390/bioengineering10020173.

[6] S. Wu et al., "ASCancer Atlas: a comprehensive knowledgebase of alternative splicing in human cancers," Nucleic Acids Research, vol. 51, no. D1, pp. D1196–D1204, Nov. 2022, doi: 10.1093/nar/gkac955.

[7] K. Kobayashi, A. Bolatkan, S. Shiina, and R. Hamamoto, "Fully-Connected Neural Networks with Reduced Parameterization for Predicting Histological Types of Lung Cancer from Somatic Mutations," Biomolecules, vol. 10, no. 9, p. 1249, Aug. 2020, doi:10.3390/biom10091249.

[8] J. Jayaram, Y. Kulkarni, L. V. Ganesh, P. Naveen, and E. A. Anaam, "Treatment Recommendation using BERT Personalization," Journal of Informatics and Web Engineering, vol. 3, no. 3, pp. 41–62, Oct. 2024, doi: 10.33093/jiwe.2024.3.3.3.

[9] S. Herath et al., "The Role of Circulating Biomarkers in Lung Cancer," Frontiers in Oncology, vol. 11, Jan. 2022, doi:10.3389/fonc.2021.801269.

[10] M. Sinkala, "Mutational landscape of cancer-driver genes across human cancers," Scientific Reports, vol. 13, no. 1, Aug. 2023, doi:10.1038/s41598-023-39608-2.

[11] Y. Zhang et al., "Genetic Load and Potential Mutational Meltdown in Cancer Cell Populations," Mol Biol Evol, vol. 36, no. 3, pp. 541–552, Oct. 2019, doi: 10.1093/molbev/msy231.

[12] C. Henschke et al., "Perspective on Management of Low-Dose Computed Tomography Findings on Low-Dose Computed Tomography Examinations for Lung Cancer Screening. From the International Association for the Study of Lung Cancer Early Detection and Screening Committee," Journal of Thoracic Oncology, vol. 19, no. 4, pp. 565–580, Oct. 2024, doi: 10.1016/j.jtho.2023.11.013.

[13] A. Naik and D. R. Edla, "Lung Nodule Classification on Computed Tomography Images Using Deep Learning," Wirel Pers Commun, vol. 116, no. 1, pp. 655–690, Oct. 2021, doi: 10.1007/s11277-020-07732-1.

[14] I. Toumazis, M. Bastani, S. S. Han, and S. K. Plevritis, "Risk-Based lung cancer screening: A systematic review," Lung Cancer, vol. 147, pp. 154–186, Oct. 2020, doi: 10.1016/j.lungcan.2020.07.007.

[15] D. M. Abdullah and A. M. Abdulazeez, "Machine Learning Applications based on SVM Classification A Review," Qubahan Academic Journal, vol. 1, no. 2, pp. 81–90, Oct. 2021, doi: 10.48161/qaj.v1n2a50.

[16] R. V. Adiraju and S. Elias, "A survey on lung CT datasets and research trends," Research on Biomedical Engineering, vol. 37, no. 2, pp. 403–418, Oct. 2021, doi: 10.1007/s42600-021-00138-3.

[17] C. M. Rudin, E. Brambilla, C. Faivre-Finn, and J. Sage, "Small-cell lung cancer," Nat Rev Dis Primers, vol. 7, no. 1, p. 3, Oct. 2021, doi:10.1038/s41572-020-00235-0.

[18] M. Mamun, A. Farjana, M. Al Mamun, and M. S. Ahammed, "Lung cancer prediction model using ensemble learning techniques and a systematic review analysis," in 2022 IEEE World AI IoT Congress (AIIoT), IEEE, Oct. 2022, pp. 187–193. doi:10.1109/AIIoT54504.2022.9817326.

[19] R. Nooreldeen and H. Bach, "Current and Future Development in Lung Cancer Diagnosis," Int J Mol Sci, vol. 22, no. 16, p. 8661, Oct. 2021, doi:10.3390/ijms22168661.

[20] J. R. Kratz et al., "Genetic and immunologic features of recurrent stage I lung adenocarcinoma," Sci Rep, vol. 11, no. 1, p. 23690, Oct. 2021, doi:10.1038/s41598-021-02946-0.

[21] R. C. Hardie, A. T. Trout, J. R. Dillman, B. N. Narayanan, and A. A. Tanimoto, "Performance of Lung-Nodule Computer-Aided Detection Systems on Standard-Dose and Low-Dose Pediatric CT Scans: An Intraindividual Comparison," American Journal of Roentgenology, Oct. 2024, doi: 10.2214/AJR.24.31972.

[22] M. Oudkerk, S. Liu, M. A. Heuvelmans, J. E. Walter, and J. K. Field, "Lung cancer LDCT screening and mortality reduction — evidence, pitfalls and future perspectives," Nat Rev Clin Oncol, vol. 18, no. 3, pp. 135–151, Oct. 2021, doi: 10.1038/s41571-020-00432-6.

[23] A. Takamatsu, M. Ueno, K. Yoshida, T. Kobayashi, S. Kobayashi, and T. Gabata, "Performance of artificial intelligence-based software for the automatic detection of lung lesions on chest radiographs of patients with suspected lung cancer," Jpn J Radiol, vol. 42, no. 3, pp. 291–299, Oct. 2024, doi: 10.1007/s11604-023-01503-1.

[24] H. Jin, C. Yu, Z. Gong, R. Zheng, Y. Zhao, and Q. Fu, "Machine learning techniques for pulmonary nodule computer-aided diagnosis using CT images: A systematic review," Biomed Signal Process Control, vol. 79, p. 104104, Oct. 2023, doi: 10.1016/j.bspc.2022.104104.

[25] Q. Zeng, Y. Xie, Z. Lu, and Y. Xia, "A human-in-the-loop method for pulmonary nodule detection in CT scans," Visual Intelligence, vol. 2, no. 1, p. 19, Oct. 2024, doi: 10.1007/s44267-024-00052-z.

[26] C. Wang et al., "Data-driven risk stratification and precision management of pulmonary nodules detected on chest computed tomography," Nat Med, Oct. 2024, doi: 10.1038/s41591-024-03211-3.

[27] G. Sidorenkov et al., "Multi-source data approach for personalized outcome prediction in lung cancer screening: update from the NELSON trial," Eur J Epidemiol, vol. 38, no. 4, pp. 445–454, Oct. 2023, doi:10.1007/s10654-023-00975-9.

[28] P. A. Grenier, "Cure Rate of Lung Cancer Diagnosed at Annual CT Screening," Radiology, vol. 309, no. 2, Oct. 2023, doi:10.1148/radiol.232698.

[29] R. J. Suji, S. S. Bhadauria, and W. W. Godfrey, "A survey and taxonomy of 2.5D approaches for lung segmentation and nodule detection in CT images," Comput Biol Med, vol. 165, p. 107437, Oct. 2023, doi:10.1016/j.compbiomed.2023.107437.

[30] C. C. Chai, W. H. Khoh, Y. H. Pang, and H. Y. Yap, "A Lung Cancer Detection with Pre-Trained CNN Models," Journal of Informatics and Web Engineering, vol. 3, no. 1, pp. 41–54, Oct. 2024, doi:10.33093/jiwe.2024.3.1.3.

[31] A. Heidari, D. Javaheri, S. Toumaj, N. J. Navimipour, M. Rezaei, and M. Unal, "A new lung cancer detection method based on the chest CT images using Federated Learning and blockchain systems," Artif Intell Med, vol. 141, p. 102572, Oct. 2023, doi: 10.1016/j.artmed.2023.102572.

[32] M. Y. B. Murthy, A. Koteswararao, and M. S. Babu, "Adaptive fuzzy deformable fusion and optimized CNN with ensemble classification for automated brain tumor diagnosis," Biomed Eng Lett, vol. 12, no. 1, pp. 37–58, Oct. 2022, doi: 10.1007/s13534-021-00209-5.

[33] R. Mehrotra, M. A. Ansari, R. Agrawal, and R. S. Anand, "A Transfer Learning approach for AI-based classification of brain tumors," Machine Learning with Applications, vol. 2, p. 100003, Oct. 2020, doi:10.1016/j.mlwa.2020.100003.

[34] M. M. Badža and M. Č. Barjaktarović, "Classification of Brain Tumors from MRI Images Using a Convolutional Neural Network," Applied Sciences, vol. 10, no. 6, p. 1999, Oct. 2020, doi: 10.3390/app10061999.

[35] R. Hashemzehi, S. J. S. Mahdavi, M. Kheirabadi, and S. R. Kamel, "Detection of brain tumors from MRI images base on deep learning using hybrid model CNN and NADE," Biocybern Biomed Eng, vol. 40, no. 3, pp. 1225–1232, Oct. 2020, doi: 10.1016/j.bbe.2020.06.001.

[36] M. O. Khairandish, M. Sharma, V. Jain, J. M. Chatterjee, and N. Z. Jhanjhi, "A Hybrid CNN-SVM Threshold Segmentation Approach for Tumor Detection and Classification of MRI Brain Images," IRBM, vol. 43, no. 4, pp. 290–299, Oct. 2022, doi: 10.1016/j.irbm.2021.06.003.

[37] T. Rahman and M. S. Islam, "MRI brain tumor detection and classification using parallel deep convolutional neural networks," Measurement: Sensors, vol. 26, p. 100694, Oct. 2023, doi:10.1016/j.measen.2023.100694.

[38] J. Amin, M. Sharif, M. Raza, T. Saba, and M. A. Anjum, "Brain tumor detection using statistical and machine learning method," Comput Methods Programs Biomed, vol. 177, pp. 69–79, Oct. 2019, doi:10.1016/j.cmpb.2019.05.015.

[39] M. Mir et al., "Detection and isolation of brain tumors in cancer patients using neural network techniques in MRI images," Sci Rep, vol. 14, no. 1, p. 23341, Oct. 2024, doi: 10.1038/s41598-024-68567-5.

[40] J. Amin, M. Sharif, M. Yasmin, and S. L. Fernandes, "A distinctive approach in brain tumor detection and classification using MRI," Pattern Recognit Lett, vol. 139, pp. 118–127, Oct. 2020, doi:10.1016/j.patrec.2017.10.036.

[41] G. Kumawat, S. K. Vishwakarma, P. Chakrabarti, P. Chittora, T. Chakrabarti, and J. C.-W. Lin, "Prognosis of Cervical Cancer Disease by Applying Machine Learning Techniques," Journal of Circuits, Systems and Computers, vol. 32, no. 01, Oct. 2023, doi:10.1142/S0218126623500196.

[42] J. Lu, E. Song, A. Ghoneim, and M. Alrashoud, "Machine learning for assisting cervical cancer diagnosis: An ensemble approach," Future Generation Computer Systems, vol. 106, pp. 199–205, Oct. 2020, doi:10.1016/j.future.2019.12.033.

[43] N. Al Mudawi and A. Alazeb, "A Model for Predicting Cervical Cancer Using Machine Learning Algorithms," Sensors, vol. 22, no. 11, p. 4132, Oct. 2022, doi: 10.3390/s22114132.

[44] S. Fekri-Ershad and S. Ramakrishnan, "Cervical cancer diagnosis based on modified uniform local ternary patterns and feed forward multilayer network optimized by genetic algorithm," Comput Biol Med, vol. 144, p. 105392, Oct. 2022, doi: 10.1016/j.compbiomed.2022.105392.

[45] T. Vaiyapuri et al., "Modified metaheuristics with stacked sparse denoising autoencoder model for cervical cancer classification," Computers and Electrical Engineering, vol. 103, p. 108292, Oct. 2022, doi: 10.1016/j.compeleceng.2022.108292.

[46] P. Jiang et al., "A systematic review of deep learning-based cervical cytology screening: from cell identification to whole slide image analysis," Artif Intell Rev, vol. 56, no. S2, pp. 2687–2758, Oct. 2023, doi: 10.1007/s10462-023-10588-z.

[47] A. Ghoneim, G. Muhammad, and M. S. Hossain, "Cervical cancer classification using convolutional neural networks and extreme learning machines," Future Generation Computer Systems, vol. 102, pp. 643–649, Oct. 2020, doi: 10.1016/j.future.2019.09.015.

[48] C. A. M. Ramirez, M. Greenop, Y. A. Almoshawah, P. L. M. Hirsch, and I. U. Rehman, "Advancing cervical cancer diagnosis and screening with spectroscopy and machine learning," Expert Rev Mol Diagn, vol. 23, no. 5, pp. 375–390, Oct. 2023, doi: 10.1080/14737159.2023.2203816.

[49] L. Zhang, L. Lu, I. Nogues, R. M. Summers, S. Liu, and J. Yao, "DeepPap: Deep Convolutional Networks for Cervical Cell Classification," IEEE J Biomed Health Inform, vol. 21, no. 6, pp. 1633–1643, Oct. 2017, doi: 10.1109/JBHI.2017.2705583.

[50] Y. Song et al., "A deep learning based framework for accurate segmentation of cervical cytoplasm and nuclei," in 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, IEEE, Oct. 2014, pp. 2903–2906. doi:10.1109/EMBC.2014.6944230.

[51] J. Zhang and Y. Liu, "Cervical Cancer Detection Using SVM Based Feature Screening," 2004, pp. 873–880. doi: 10.1007/978-3-540-30136-3_106.

[52] F. Afza, M. Sharif, M. Mittal, M. A. Khan, and D. J. Hemanth, "A hierarchical three-step superpixels and deep learning framework for skin lesion classification," Methods, vol. 202, pp. 88–102, Oct. 2022, doi:10.1016/j.ymeth.2021.02.013.

[53] D. Bi, D. Zhu, F. R. Sheykhahmad, and M. Qiao, "Computer-aided skin cancer diagnosis based on a New meta-heuristic algorithm combined with support vector method," Biomed Signal Process Control, vol. 68, p. 102631, Oct. 2021, doi: 10.1016/j.bspc.2021.102631.

[54] P. P. Tumpa and M. A. Kabir, "An artificial neural network based detection and classification of melanoma skin cancer using hybrid texture features," Sensors International, vol. 2, p. 100128, 2021, doi:10.1016/j.sintl.2021.100128.

[55] E. M. Senan and M. E. Jadhav, "Analysis of dermoscopy images by using ABCD rule for early detection of skin cancer," Global Transitions Proceedings, vol. 2, no. 1, pp. 1–7, Oct. 2021, doi:10.1016/j.gltp.2021.01.001.

[56] M. Toğaçar, Z. Cömert, and B. Ergen, "Intelligent skin cancer detection applying autoencoder, MobileNetV2 and spiking neural networks," Chaos Solitons Fractals, vol. 144, p. 110714, Oct. 2021, doi:10.1016/j.chaos.2021.110714.

[57] R. Mohakud and R. Dash, "Designing a grey wolf optimization based hyper-parameter optimized convolutional neural network classifier for skin cancer detection," Journal of King Saud University - Computer and Information Sciences, vol. 34, no. 8, pp. 6280–6291, Oct. 2022, doi:10.1016/j.jksuci.2021.05.012.

[58] S. Saravanan, B. Heshma, A. V. A. Shanofer, and R. Vanithamani, "Skin cancer detection using dermoscope images," Mater Today Proc, vol. 33, pp. 4823–4827, 2020, doi: 10.1016/j.matpr.2020.08.388.

[59] D. C. Malo, Md. M. Rahman, J. Mahbub, and M. M. Khan, "Skin Cancer Detection using Convolutional Neural Network," in 2022 IEEE 12th Annual Computing and Communication Workshop and Conference (CCWC), IEEE, Oct. 2022, pp. 169–176. doi:10.1109/CCWC54503.2022.9720751.

[60] B. Harangi, "Skin lesion classification with ensembles of deep convolutional neural networks," J Biomed Inform, vol. 86, pp. 25–32, Oct. 2018, doi: 10.1016/j.jbi.2018.08.006.

[61] B. Shetty, R. Fernandes, A. P. Rodrigues, R. Chengoden, S. Bhattacharya, and K. Lakshmanna, "Skin lesion classification of dermoscopic images using machine learning and convolutional neural network," Sci Rep, vol. 12, no. 1, p. 18134, Oct. 2022, doi:10.1038/s41598-022-22644-9.

[62] A. Esteva et al., "Dermatologist-level classification of skin cancer with deep neural networks," Nature, vol. 542, no. 7639, pp. 115–118, Oct. 2017, doi: 10.1038/nature21056.

[63] T. Kavitha et al., "Deep Learning Based Capsule Neural Network Model for Breast Cancer Diagnosis Using Mammogram Images," Interdiscip Sci, vol. 14, no. 1, pp. 113–129, Oct. 2022, doi: 10.1007/s12539-021-00467-y.

[64] M. Ragab, A. Albukhari, J. Alyami, and R. F. Mansour, "Ensemble Deep-Learning-Enabled Clinical Decision Support System for Breast Cancer Diagnosis and Classification on Ultrasound Images," Biology (Basel), vol. 11, no. 3, p. 439, Oct. 2022, doi: 10.3390/biology11030439.

[65] R. Sánchez-Cauce, J. Pérez-Martín, and M. Luque, "Multi-input convolutional neural network for breast cancer detection using thermal images and clinical data," Comput Methods Programs Biomed, vol. 204, p. 106045, Oct. 2021, doi: 10.1016/j.cmpb.2021.106045.

[66] M. Kashif, K. R. Malik, S. Jabbar, and J. Chaudhry, "Application of machine learning and image processing for detection of breast cancer," in Innovation in Health Informatics, Elsevier, 2020, pp. 145–162. doi:10.1016/B978-0-12-819043-2.00006-X.

[67] D. A. Ragab, M. Sharkas, S. Marshall, and J. Ren, "Breast cancer detection using deep convolutional neural networks and support vector machines," PeerJ, vol. 7, p. e6201, Oct. 2019, doi: 10.7717/peerj.6201.

[68] S. Khan, N. Islam, Z. Jan, I. U. Din, and J. J. P. C. Rodrigues, "A novel deep learning based framework for the detection and classification of breast cancer using transfer learning," Pattern Recognit Lett, vol. 125, pp. 1–6, Oct. 2019, doi: 10.1016/j.patrec.2019.03.022.

[69] S. Guan and M. Loew, "Using generative adversarial networks and transfer learning for breast cancer detection by convolutional neural networks," in Medical Imaging 2019: Imaging Informatics for Healthcare, Research, and Applications, P. R. Bak and P.-H. Chen, Eds., SPIE, Oct. 2019, p. 48. doi: 10.1117/12.2512671.

[70] D. Selvathi and A. A. Poornila, "Deep Learning Techniques for Breast Cancer Detection Using Medical Image Analysis," 2018, pp. 159–186. doi: 10.1007/978-3-319-61316-1_8.

[71] S. A. Mojarad, S. S. Dlay, W. L. Woo, and G. V Sherbet, “Breast cancer prediction and cross validation using multilayer perceptron neural networks,” in 2010 7th International Symposium on Communication Systems, Networks & Digital Signal Processing (CSNDSP 2010), IEEE, Oct. 2010, pp. 760–764. doi: 10.1109/CSNDSP16145.2010.5580318.

[72] A. Das, M. N. Mohanty, P. K. Mallick, P. Tiwari, K. Muhammad, and H. Zhu, “Breast cancer detection using an ensemble deep learning method,” Biomed Signal Process Control, vol. 70, p. 103009, Oct. 2021, doi:10.1016/j.bspc.2021.103009.

[73] A. K. Ali, A. M. Abdullah, and S. F. Raheem, “Impact the Classes’ Number on the Convolutional Neural Networks Performance for Image Classification,” International Journal of Advanced Science Computing and Engineering, vol. 6, no. 2, pp. 64–69, Oct. 2024, doi:10.62527/ijasce.6.2.204.

[74] A. LG and E. AT, “Using Three Machine Learning Techniques for Predicting Breast Cancer Recurrence,” J Health Med Inform, vol. 04, no. 02, 2013, doi: 10.4172/2157-7420.1000124.

[75] Md. A. H. Sujon and H. Mustafa, “Comparative Study of Machine Learning Models on Multiple Breast Cancer Datasets,” International Journal of Advanced Science Computing and Engineering, vol. 5, no. 1, pp. 15–24, Oct. 2023, doi: 10.62527/ijasce.5.1.105.

[76] D. Wang, J.-R. Li, Y.-H. Zhang, L. Chen, T. Huang, and Y.-D. Cai, “Identification of Differentially Expressed Genes between Original Breast Cancer and Xenograft Using Machine Learning Algorithms,” Genes (Basel), vol. 9, no. 3, p. 155, Oct. 2018, doi:10.3390/genes9030155.

[77] S. K. Mohamed, N. A. Sakr, and N. A. Hikal, “A Review of Breast Cancer Classification and Detection Techniques,” International Journal of Advanced Science Computing and Engineering, vol. 3, no. 3, pp. 128–139, Oct. 2021, doi: 10.62527/ijasce.3.3.55.

[78] C. L. A. Dewald et al., “Automated Classification of Free-Text Radiology Reports: Using Different Feature Extraction Methods to Identify Fractures of the Distal Fibula,” RöFo - Fortschritte auf dem Gebiet der Röntgenstrahlen und der bildgebenden Verfahren, vol. 195, no. 08, pp. 713–719, Oct. 2023, doi: 10.1055/a-2061-6562.

[79] D. Karimi et al., “Learning to Detect Brain Lesions from Noisy Annotations,” in 2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI), IEEE, Oct. 2020, pp. 1910–1914. doi:10.1109/ISBI45749.2020.9098599.

[80] M. Z. Khaliki and M. S. Başarslan, “Brain tumor detection from images and comparison with transfer learning methods and 3-layer CNN,” Sci Rep, vol. 14, no. 1, p. 2664, Oct. 2024, doi: 10.1038/s41598-024-52823-9.

[81] W. Bismi, D. Riana, and A. S. Hewiz, “Disease Identification on Fig Leaf Images Using Deep Learning Method,” International Journal of Advanced Science Computing and Engineering, vol. 6, no. 2, pp. 57–63, Oct. 2024, doi: 10.62527/ijasce.6.2.203.

[82] D. Meidelfi, - Hendrick, F. Sukma, and S. Y. Kharisma, “Analysis of Eye Disease Classification by Comparison of the Random Forest Method and K-Nearest Neighbor Method,” International Journal of Advanced Science Computing and Engineering, vol. 5, no. 2, pp. 136–145, Oct. 2023, doi: 10.62527/ijasce.5.2.151.

[83] J.-R. Lee, K.-W. Ng, and Y.-J. Yoong, “Face and Facial Expressions Recognition System for Blind People Using ResNet50 Architecture and CNN,” Journal of Informatics and Web Engineering, vol. 2, no. 2, pp. 284–298, Oct. 2023, doi: 10.33093/jiwe.2023.2.2.20.

[84] Z. Qin, H. Ye, G. Y. Li, and B.-H. F. Juang, “Deep Learning in Physical Layer Communications,” IEEE Wirel Commun, vol. 26, no. 2, pp. 93–99, Oct. 2019, doi: 10.1109/MWC.2019.1800601.

[85] W. Meyerson, J. Leisman, F. C. P. Navarro, and M. Gerstein, “Origins and characterization of variants shared between databases of somatic and germline human mutations,” BMC Bioinformatics, vol. 21, no. 1, p. 227, Dec. 2020, doi: 10.1186/s12859-020-3508-8.

[86] P. A. S. Rani and N. S. Singh, “Paddy Leaf Symptom-based Disease Classification Using Deep CNN with ResNet-50,” International Journal of Advanced Science Computing and Engineering, vol. 4, no. 2, pp. 88–94, Oct. 2022, doi: 10.62527/ijasce.4.2.83.

[87] R. L. Siegel, K. D. Miller, N. S. Wagle, and A. Jemal, “Cancer statistics, 2023,” CA Cancer J Clin, vol. 73, no. 1, pp. 17–48, Oct. 2023, doi:10.3322/caac.21763.

[88] Y. H. Gan, S. Y. Ooi, Y. H. Pang, Y. H. Tay, and Q. F. Yeo, “Facial Skin Analysis in Malaysians using YOLOv5: A Deep Learning Perspective,” Journal of Informatics and Web Engineering, vol. 3, no. 2, pp. 1–18, Oct. 2024, doi: 10.33093/jiwe.2023.3.2.1.

[89] J. S. A. Tan, Z. C. Embi, and N. Hashim, “Comparison of Machine Learning Methods for Calories Burn Prediction,” Journal of Informatics and Web Engineering, vol. 3, no. 1, pp. 182–191, Oct. 2024, doi:10.33093/jiwe.2024.3.1.12.

[90] H. Zeng et al., “Cancer survival statistics in China 2019–2021: a multicenter, population-based study,” Journal of the National Cancer Center, vol. 4, no. 3, pp. 203–213, Sep. 2024, doi:10.1016/j.jncc.2024.06.005.

[91] A. M. Sebastian and D. Peter, “Artificial Intelligence in Cancer Research: Trends, Challenges and Future Directions,” Life, vol. 12, no. 12, p. 1991, Nov. 2022, doi: 10.3390/life12121991.

[92] R. L. Siegel, A. N. Giaquinto, and A. Jemal, “Cancer statistics, 2024,” CA Cancer J Clin, vol. 74, no. 1, pp. 12–49, Jan. 2024, doi:10.3322/caac.21820.