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Deep Learning in Oncology: A Survey of Architectures for Cancer Detection and Classification

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Abstract: Deep learning, in particular Convolutional Neural Networks (CNNs), have begun to serve as a great asset for improving many aspects in oncology including cancer detection, diagnosis, and treatment. This survey paper presents an overview of the works that employed CNN-based techniques towards the early detection of different cancers i.e. breast, lung, prostate and skin cancer. We investigate the application of CNN on medical image processing, primarily for radiographic imaging, including CTs, MRIs, and histopathological sections. Paper considers the actual studies devoted to the development of new CNN architectures, image preprocessing techniques, and transfer learning approaches aimed at increasing the cancer detection systems accuracy and efficiency.

Nevertheless, a number of issues still need to be resolved, such as the high expense of acquiring high-quality data, the inability of deep learning models to be interpreted, and the requirement for big annotated datasets. Additionally, the survey article shows how CNNs could be used to increase the accuracy of cancer diagnosis when combined with other machine learning and imaging methods like multimodal imaging and genomics. Finally, the survey discusses the direction of subsequent research in the use of CNNs in oncology, including applying clinical workflows, diagnostics, and precision medicine in all its aspects.

Keywords: Deep - learning, Oncology, CNN Architectures, Classification, Cancer Detection, pre trained CNN Network

I.INTRODUCTION

Cancer includes a number of disorders that result in uncontrolled cell division which has the ability to infiltrate and destroy healthy tissues. It is due to genetic alterations and external factors and can be found in different regions of the body. Over 100 distinct types of cancers have been categorized so far. There are severe physical symptoms such as pain, loss of appetite as well as anxiety and depression that quite deeply affect not only the individual but also members of society due to the interference of their intense medical needs, expensive expenses and relationships.

As per the information available on the American Cancers Society, it is anticipated that in the year 2024 there will be 2001140 new cases diagnosed as cancer and 609,720 deaths because of it in the United States[1]**.** One of the reasons for people surviving even after being diagnosed with cancer is because they are being screened at an earlier stage than before, however the American's Cancer mortality rate had dropped overall by a significant number of 4 million with people not smoking being the only exception. Some cancer cases are on the rise which may cause trouble. Between 2015 to 2019 the rate of cancer diagnosis increased for breast, pancreas and uterus by 0.6% to 1% and 2% for prostate, female liver, kidney, HPV, oral and melanoma by 3%.

Many treatments and the likelihood of long-term survival can be improved if a cancerous disease is diagnosed at an early stage. In this case, the treatment is less aggressive, and consequently lung cancer patients have higher chances of survival. An early diagnosis of lung cancer can be achieved by means of treatment or check-ups.

Many industries including health care have been transformed using technologies such as artificial intelligence or AI that are used in a smart city. For instance, in healthcare, AI has given physician's the opportunity to detect almost any type of cancers using screening methods such as computer-aided diagnosis orCAD systems.

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These are highly sophisticated systems that can be trained using images from x-rays, MRIs and CT scans to search and detect anomalous changes that might lead towards cancer. CAD systems are like virtual assistants that scan images for errors and work through large data over short periods of time.

One of the domains where Machine Learning (ML), which is one of the sub-domains of AI, stands out. ML computer systems are capable of scrutinising volumes and complexities of data sets and often uncover trends which routinary methods may not consider. Deep Learning (DL) which is a subset of ML is more sophisticated as it processes and analyzes medical images through neural networks to the extent of detecting the most minuscule detail that a human Being would miss. These technologies are critical especially in dealing with the increasing volume of data.

II.THEORETICAL BACKGROUND

Deep learning has become a potent instrument in the medical domain, especially in cancer research, being a branch of AI with excellent capabilities over time to analyze overly complicated data with a high number of dimensions and limited human intervention. Deep learning models do not require identifying feature extraction as they learn the features from natural data, which qualifies them to outperform conventional techniques for jobs like cancer categorization and detection. Ultimately, the advancements in deep learning are heavily applied in the oncology segment, where a minor error in diagnosing or classifying the type of cancer would significantly affect the treatment journey [2].

Another place where deep learning has found use is in detecting cancer through images. Convolutional Neural Networks (CNNs) for example have been incredibly efficient in assisting doctors analyze mammograms, CT scans, MRIs as well as their variants. These models, for instance, detect and accurately segment regions of interest including the tumors and relevant metastases. The U-Net model provides accurate image segmentation of biomedicinal images, and is consequently adopted broadly in the detection of cancerous tumors during radiotherapy [3]. Correspondingly, it has been established through investigation that CNNs are capable of perceiving structures in imaging data that are microscopically invisible to the naked human eye [4].

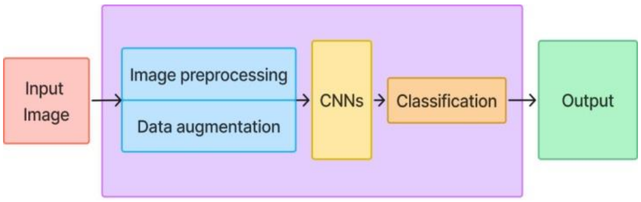

Fig. 1 The generalized block diagram DL-based methods

Besides medical images, deep learning also goes to the level of comprehensive genomic and molecular data analysis. Recurrent neural networks (RNN's) as well as transformer-based architectures are again employed for the analysis of genetic alterations, RNA sequencing data and proteomic profiles envisaged for subtyping and prognosis of cancer. The development of multimodal deep learning models that combined imaging and genomic data and this was able to provide a better insight into cancer biology and thus enable tailored treatment options [5]. Also, in Cut-E and Cohen's (2018) study, deep learning models were reported to have been trained with CNNs and WSIs that automate the classification of tissue samples as malignant or benign using conversion of gigapixel images of full-tissue sections. This work was supported by, who were also able to perform near the level of pathologists using a CNN-based model[5].
Integrating artificial intelligence into oncology also makes a lot of sense. It increases the speed of diagnosis, decreases inter-observer differences and uses health care personnel efficiently by offloading monotonous tasks. There are also however obstacles to the success of integration such as the existence of considerable volumes of annotated datasets required for training, explaining the model to clinicians to resolve trust issues, and removing the biases in the datasets.

III.CANCER DETECTION TECHNIQUES

Figure 2 provides an in-depth breakdown of various cancer types and how these cancers can be detected through medical imaging and deep learning. First it divides cancers by human body systems. The reproductive system includes breast, cervical, ovarian, and prostate cancers; the digestive system includes esophageal, liver, pancreatic, and colon cancers; the respiratory system includes lung and oral cancers; and other cancers include brain and skin.

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Medical imaging, including pathology procedures, histological and cytological imaging, and radiology techniques such as X-ray, ultrasound, MRI, CT, and PET, is taken into consideration with the objective of detecting cancer. In orderto increase the overall quality of the images, the imaging program also includes a preprocessing step that includes rescaling, normalization, augmentation, noise reduction, and enhancement.

The next step involves the application of different deep neural networks which varieties include CNNs, RCNNs, RNNs, GANs and hybrid models. Furthermore, transfer learning has been used as a strategy to give pre-trained models like ResNet, VGGNet, Inception, MobileNet, and AlexNet more depth.And lastly to measure how well the cancer detection system performed several evaluation techniques pertaining to measurement of accuracy and efficiency such as accuracy, precision, Recall, F1-score, AUC-ROC.

Canonicalization plays a crucial role as it not only highlights the importance of combining high-quality images with sophisticated deep neural network architectures, but also uses the best approach to help improve the research work on cancer detection and classification.

A. Medical imaging techniques

The potential of medical imaging technology is very high in both radiology and pathology which greatly assists the practice of diagnosing and treating a multitude of diseases such as cancer. For instance, delineate the role of radiology as one of providing images focusing on the internal parts of the body through various techniques while pathology embarks on evaluating tissues, cells and organs for any aberrations [6]. A good example pertains to pathological techniques of histopathology that involve treating the tissues with dye for disease traces at the cellular level while cytopathology deals with cells found in body fluids or aspirated by thin needles. This study is devoted to medical radiology[7] and emphasizes some of the imaging methods including X-rays, Computed Tomography (CT) scans, Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET) scans, and ultrasound.

1) X-radiation (X-Ray):

X-ray radiography is a useful tool for medical and surgical planning, as well as for directing treatments like catheter and stent placements, due to its many benefits, which include being non-invasive, rapid, and painless. However, there are risks associated with it, like exposure to ionizing radiation, which can raise the risk of cancer and damage tissue, leading to reddening of the skin, cataracts, and hair loss at high radiation levels. Its clinical uses are numerous and include mammography for breast cancer screening, projectional radiography for fracture and lung ailment diagnosis, and chiropractic and dental examinations.

2) Magnetic resonance imaging (MRI*):*

Magnetic Resonance Imaging (MRI) is a non-invasive technique that creates detailed images of the body's internal structures using strong magnets and radio waves. Because MRI doesn't use dangerous radiation like X-rays and CT scans do, it may be a safer choice for some people.It's commonly used to diagnose and monitor issues with the brain, spine, muscles, joints, and organs. MRI is especially useful for detecting tumors, neurological problems, and injuries to the musculoskeletal system, providing clear images that help doctors make accurate diagnoses and treatment plans

3) Computed tomography Scan (CT):

The CT is a powerful imaging tool that utilizes both X-rays and a computer to produce transverse images of the body One of these 3-D pictures portrays almost 3D circulation of veins, neural net, and bones of the target area. It is painless and also ultra-fast. It can also detect small density changes with the use of a cross-sectional ultrasound scan without the need for catheterisation of arteries However, CT possesses limitations such as exposure to harmful radiation, does not provide real-time imaging and also difficulties in the identification of certain intra- luminal changes. When there is a requirement of CT, it has to be done using a contrast dye, which also has side effects like allergic reactions and has a high resolution but resolution for soft tissues is low. CT allows us to evaluate parts of the human body, and diagnose different medical conditions, injuries, and any abnormal parts, incorporate aid during surgical operations and evaluate the patients in the process of a cancer therapy.

4) Ultrasonogram (US):

Ultrasonography can generate images of the body's internal structures, abdomen or even a foot by utilizing high frequency sound beams which are reflected off various tissues. It also works great detecting variations in flow and abnormalities of flow both within a vessel as well as outside of it. It is also painless and extremely risk free and able to provide real-time images. While there are no set guidelines as such, there are some limitations keeping in mind of the operator and also the time required to perform the procedure, its ability to visualize solid organs in the abdomen, including the liver, pancreas, and kidney as well as embryonic development and head and neck structures, is essential for the detection of cancer.

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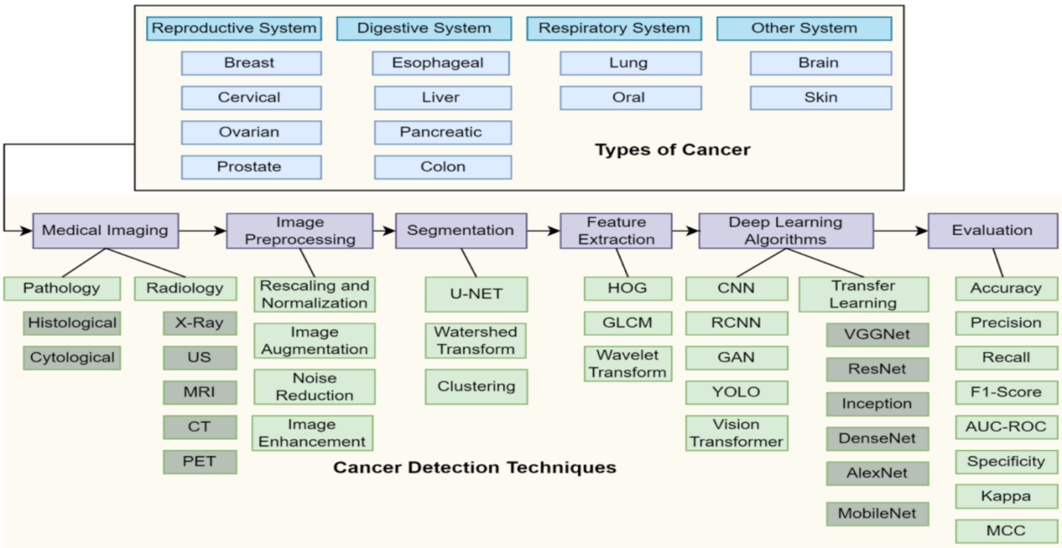

Fig. 2 Systematic Workflow for Cancer Detection [8]

This technology is useful in detecting tumors, cysts as well as abnormalities which may bring about risks of possible cancer.

5) Positron emission tomography (PET):

PET (Positron Emission Tomography) is a potent method for detecting cancer since it tracks the body's metabolic activities using radiotracers.It is noninvasive and provides real-time functional information, enabling the identification of abnormal metabolic activity associated with cancer. PET scans are very useful for identifying micro cancers, determining metastases, and evaluating how well cancer treatments are working. PET scans have an advantage over CT and MRI, which concentrate on structural information, in that they can identify metabolic changes at the cellular level, even if they expose users to ionizing radiation since they employ radioactive chemicals. By combining metabolic information with anatomical pictures, PET/CT improves cancer monitoring and detection.

B. Preprocessing

Deep learning models rarely rely on raw input data, as it needs to be improved to be more relevant so that the model can perform with better efficiency. Most deep learning models preprocess data before feeding it into the model for training. For instance, in oncology, depending on the data types used to detect and classify cancer, a variety of techniques are implemented in preprocessing, if it is medical imaging for example, Plain transformations are usually performed during the pre-processing phase. For instance, normalization, which reduces the pixel values to an accepted range (e.g. between 0 and 1) to minimize bias and improve learning. Another term that is familiar in deep learning is data augmentation where the common approach rotates, flips, or zooms in pictures so as to enlarge the dataset making it versatile while reducing overfitting [9].In order to capture the specific tumor using the MRI imaging, noise filtering techniques such as Gaussian or Wiener filters are also implemented to make the MRI images more accurate[10]. Also important is the fact that images are usually resized to specific inputs of the model and the model can also utilize feature selection to highlight the most significant attributes within the input (such as attributes depicting how a tumor is seen in images) that are likely to improve the model’s performance in predicting the output[4]. Participating in all of this is, naturally, proper processing of data which guarantees better results when the model is used for cancer detection.

IV.EXISTING TECHNIQUES

A. Deep learning algorithms

1) Convolutional neural network:

Convolutional Neural Networks (CNNs) have become a popular choice for cancer detection and segmentation due to their ability to effectively extract valuable features and recognize complex patterns in medical images[11]. Specifically, CNN architectures are designed to process various types of medical imaging, including MRI, CT scans, and histopathology slides. These networks consist of multiple layers that can independently identify key features such as tumor boundaries, textures, and shapes. Pooling layers come after the convolutional layers to decrease spatial dimensions and computational load, while maintaining essential features.

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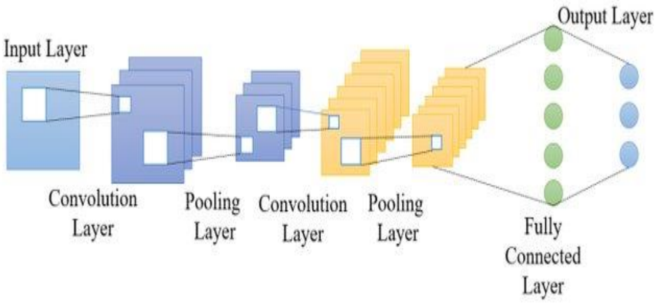

Fig. 3 Basic architecture of CNN [12].

Advanced CNN models, like U-Net, utilize fully connected layers, upsampling, and skip connections to accurately delineate malignant regions in images. By training on annotated datasets, CNNs can differentiate between benign and malignant tissues, enabling precise tumor detection and classification. This significantly aids in cancer diagnosis, treatment planning, and monitoring disease progression. Additionally, to optimize the performance of CNNs, automatic hyperparameter tuning techniques such as Grey Wolf Optimization (GWO)[13], Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Chimp Optimization Algorithm (COA) are commonly used[14]. Hybrid optimization algorithms, like PSOBER, a combination of PSO and the Al-Biruni Earth Radius (BER) algorithm[15], can further improve CNN optimization. For instance, the use of metaheuristic optimization techniques, such as the Marine Predators Algorithm (MPA), in combination with CNNs to enhance the accuracy of lung cancer detection[16].

2) YOLO:

YOLO (You Only Look Once)[17] is a relatively faster and precise real-time object detection architecture that has applications in areas like medical imaging for the diagnosis of cancer. Unlike the traditional multiple-stage structures, this exciting architecture considers all aspects of the recognition process as a single regression task where multiple boxes and their associated class probabilities are predicted simultaneously. All the convolutional layers of a one-step design structure of YOLO receive the image in its entirety, cutting down the amount of time spent on calculations up to great levels. Each cell can learn several bounding boxes together with the corresponding confidence scores and class probabilities after the image is divided into a grid structure.Such efficiency of analysis enables YOLO to perform well on speed for large medical imaging datasets.

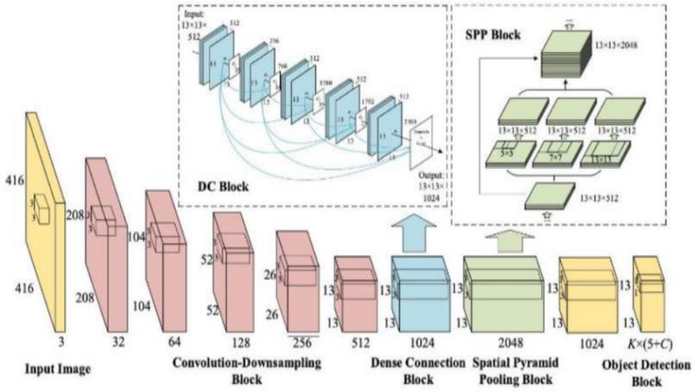

Fig. 4 The DC-SPP-YOLO Model [18].

3) Regional CNN:

Advanced CNN architectures called regional convolutional neural networks (R-CNNs) are made to identify and segment specific regions of interest (ROIs) in a picture. The original R-CNN generates site ideas through selective search, which can be then passed through a CNN for function extraction, observed via system mastering algorithms for class. Fast R-CNN[19]improves processing pace by incorporating an RoI pooling layer, permitting evaluation of the complete photograph without delay. Similar to this, Faster R-CNN (Ren, 2015) enhances efficiency by including a Region Proposal Network (RPN) to produce suggestions from function maps instantly. In order to enable distinct tumor segmentation, Mask R-CNN (He, 2017) expands on Faster R-CNN by incorporating a segmentation mask prediction problem.

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These R-CNN versions are quite effective in detecting most cancers, as it should be figuring out and localizing tumors across various imaging modalities, thereby improving diagnostic accuracy and supporting centered treatment planning.

4) Generative adversarial networks:

The two components of Generative Adversarial Networks (GANs) techniques are a generator, which generates data, and a discriminator, which classifies whether the data is real or generated [20]. A process of jointly training the models allows to improve the generator such that its outputs are as close as possible to real data. The significance of GANs in cancer diagnostics comes from the fact that they can create realistic synthetic medical images. These can help augment the training data and thus enhance the capabilities of diagnosis models. Since GANs are capable of generating realistic tumor images by learning the detailed structure of data distributions, such images can help improve the performance of CNNs for cancer detection and segmentation. Besides, GANs are also instrumental in improving data augmentation methods which in turn enhance the performance and flexibility of cancer detection systems. The fact that there is the ability to synthesize realistic looking high quality medical shots helps in the early onset of the disease, guides therapy regimens, and improves cancer care overall.

B. Transfer learning

1) ResNet:

ResNet (Residual Networks)[21], is a deep convolutional neural network (CNN) with the purpose of aiding the training of very deep models via residual learning. By using skip connections, it effectively takes care of the vanishing gradient problem and thus allows building much deeper structures. ResNet-50 is made of 50 layers, which are grouped into chains of residual blocks, and each residual block contains three convolutional layers. Following the reconstruction scheme, ResNet-101 deepens the network to 101 layers by adding more residual blocks. To further enhance the model’s complexity, ResNet-152 increased depth to 152 layers, which allows more complicated feature extraction.

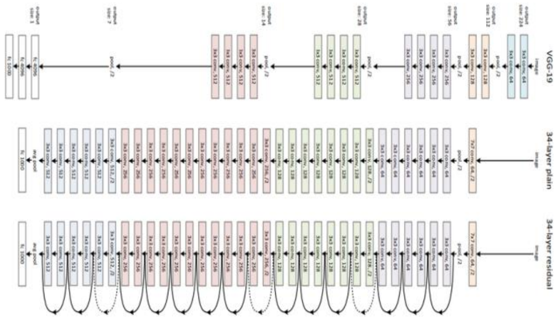

Fig. 5 ResNet architecture [22].

2) VGGNet:

The VGGNet architecture[23], is known for being quite simple in its structure, using small 3×3 convolutional filters. In terms of its versions, VGG16 and VGG19 are the two famous ones, one with more layers and more parameters to train.VGG16 has 16 weights. These include 13 convolutional layers. This is made up of three layers of 256 filters after two levels of 64 filters and two layers of 128 filters, and two ‘groups of 3 layers’ that have 512 filters each. This idea is further developed by VGG19, which has 16 convolutional layers, including two layers with 64 and 228 filters, four layers with 256 filters, and two "groups of 4 layers" with 512 filters each.The VGG 19 model has the same 3 fully connected layers however. All architectures also have 5 Max-Pooling layers (2×2) after every group of convolutional layers, if applicable, at the end of the model. Although the complexity is relatively low, the VGGNet is quite heavy to use due to the number of 3*3 filters being used. The simplicity of the model has enabled it to be widely popular and researched under medical image classification where cancer detection and classification are one of its tasks.

3) Inception:

InceptionNetV1[24], sometimes referred to as GoogLeNet[25],[26]is a complex CNN that comes with the inception module which is a significant invention geared towards increasing the performance without demanding more computations. This includes 1x1, 3x3, and 5x5 convolution operations, as well as 3x3 max pooling, where various functions work in parallel. This depth-wise combining of the tensors allows the capturing of spatial features of the network at various levels of depth, thus allowing complex pattern recognition to be achieved. The overall version of this architecture had 22 layers.The severance eventual aims were primarily differences in the number of parameters in the models being compared, a major drawback of conventional CNN. This was done using 1x1 convolutions to perform a dimensionality reduction before running high computation content.

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The purpose of these succeeding versions, InceptionV2 through V4, was to focus on modifying these convolutional sequences introducing factorized convolutions and more recently regularization modes. InceptionNet's modular and scalable design has profoundly enhanced the development of deep-learning models allowing such models to achieve higher accuracy in many computer vision tasks.

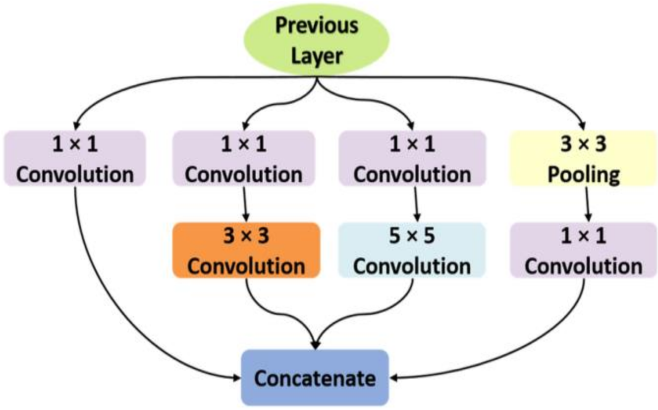

Fig. 6 Block diagram of the Inception module[27].

4) Mobile Net:

The MobileNet family of deep neural network architectures is perfect for usage in embedded systems and mobile devices because of its lightweight and efficient design, particularly for vision tasks.The main innovation behind MobileNet is the use of depth wise separable convolutions. Instead of performing a traditional convolution, which combines multiple operations at once, with this method, the procedure is divided into two easier steps: a pointwise convolution and a depth wise convolution. As a result, fewer parameters and less processing are required, making the network much more efficient[28]. There are a few versions of MobileNet, each building on the previous one. MobileNetV1, released in 2017, introduced depth wise separable convolutions. MobileNetV2, which came out in 2018, improved on this with features like inverted residuals and linear bottlenecks, making the model even faster and more efficient[29]. Additional modifications including squeeze-and-excitation modules and neural architecture search (NAS) are included in the most recent version, MobileNetV3, which was published in 2019 and further enhances performance and lowers latency [30]. Because of their efficiency, MobileNet models are particularly useful in fields like cancer detection, where high-quality image analysis is crucial but computational resources may be limited. The ability to perform real-time analysis on devices with less processing power makes MobileNet a valuable tool in clinical environments, where quick and accurate diagnoses are essential.

5) Alex Net:

With its deep convolutional neural network design, AlexNet revolutionized image processing by pushing the limits of what was previously feasible at the moment. Three fully connected layers and five convolutional layers make up the model's eight total layers [31]. Max-pooling layers are applied after specific convolutional layers to minimize the image's spatial dimensions and the amount of processing needed. A key innovation in AlexNet is its use of ReLU activations, which add non-linearity to the model. This not only speeds up training but also helps solve the vanishing gradient problem, which was a major hurdle in training deep networks. To further prevent overfitting, dropout is applied to the fully connected layers during training, effectively "dropping" random units to ensure the model doesn't become too reliant on any one part of the network. However, AlexNet's use of data augmentation and GPU acceleration was arguably its most significant innovation. These techniques allowed the model to handle the massive computational load of training on large datasets like ImageNet, which was a crucial step in the widespread adoption of deep learning.

V.EVALUATION METRICS

Evaluation metrics are used to assess how well a model performs, particularly by measuring its accuracy on new, unseen data. Four key concepts are commonly used to understand the model's performance:

- True Positive (TP): The model correctly predicted a positive outcome, and the actual result was indeed positive.
- True Negative (TN): The model correctly predicted a negative outcome, and the actual result was indeed negative.
- False Positive (FP): The model incorrectly predicted a positive outcome when the actual result was negative.
- False Negative (FN): The model incorrectly predicted a negative outcome when the actual result was positive.

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A. Accuracy

Accuracy is the percentage of correct predictions made by the model, including both true positives (TP) and true negatives (TN), out of all the predictions it makes. It gives an overall measure of how well the model is performing.

$$\text{Accuracy} = \frac{TP + TN}{TP+TN+FP+FN}$$

Let's talk about the model that is able to detect 80 malignant images and at the same time classify 90 images as non-malignant. The calculation goes as (80+90)/200=0.85 or let's say, 85%. What this did was estimate that the model dropped the ball on only 15% of the outcomes.

B. Precision

The division of the true positive count by the aggregate sum of predicted positives can also be said to be a precision score, whereas the predicted positives are made up of true positives and false positives only. It is evident that the models have sufficient intelligence to differentiate between good and negative scenarios.

$$\text{Precision} = \frac{TP}{TP+FP}$$

One hundred regions are identified as cancerous using a segmentation model, out of which 80 are true positives (genuinely cancerous), and 20 are false positives. The model's accuracy is determined by dividing 80 by the sum of the positive predictions (80 + 20), resulting in an 80% or 0.8 value. This shows that 80% of the identified cancerous regions are appropriately classified as such by the model.

C. Recall / Sensitivity

Recall (or sensitivity) is the proportion of actual positive cases that are correctly identified by the model. In other words, it measures the ability of the model to detect all relevant positive cases.

$$\text{Recall} = \frac{TP}{TP+FN}$$

In a dataset with 100 malignant areas, the model successfully identifies 80 of them but misses 20. This gives a recall of 80 / (80 + 20) = 0.8, or 80%. In simpler terms, the model is able to detect 80% of the actual malignant areas.

D. F1-score

A statistical measure known as the F1-score provides a balance between precision and recall by representing the harmonic mean of the two. When there is an unequal distribution of classes in the dataset, it is especially helpful.

$$\text{F1-score} = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}$$

The formula for the F1-score is 2 * (0.8 * 0.8) / (0.8 + 0.8) = 0.80, or 80%, with a precision of 80% and a recall of 80%. This indicates that the F1-score, which strikes a balance between recall and precision, is 80%.

E. ROC curve

The AUC-ROC is a measure of how well a model can tell the difference between positive and negative cases. The ROC curve shows how the true positive rate (recall) and false positive rate (1-specificity) change as the decision threshold varies. For example, a model for detecting cancer with an AUC-ROC of 0.95shows excellent ability to distinguish between malignant and non-cancerous areas, meaning it can accurately identify both cancerous and non-cancerous cases. An AUC of 1.0 indicates a flawless model, whereas 0.5 indicates a model that is incapable of differentiating.

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VI.ANALYSIS OF DEEP LEARNING TECHNIQUES

TABLE I ANALYSIS OF DIFFERENT CANCER DETECTION TECHNIQUES

Sr. No.	Title, Publication & year	Learning Paradigm	Method	Challenges
1	Advancing Breast Cancer Detection: Enhancing YOLOv5 Network for Accurate Classification in Mammogram Images[32].	Deep Learning	Used YOLOv5 to detect breast tumors and Mask R-CNN to identify tumor boundaries and classify as benign or malignant.	Challenges include reducing high FPR and FNR in mammography, enhancing the MCC for better overall performance, and optimizing model accuracy.
2	Improved Bald Eagle Search Optimization With Deep Learning-Based Cervical Cancer Detection and Classification[33].	Deep Learning	Combined a modified LeNet model with an attention-based LSTM network to classify cervical cancer from Pap smear images.	Addressing errors in manual screening and improving detection accuracy.
3	Design of Multiband Switching Illumination With Low-Concentration Lugol Stain for Esophageal Cancer Detection[34].	Machine Learning	Used special imaging with low-concentration Lugol stain and SVM models to detect cancerous areas in the esophagus.	Making the method less invasive while keeping it highly accurate.
4	Advancing Oncology Diagnostics: AI-Enabled Early Detection of Lung Cancer Through Hybrid Histological Image Analysis[35].	Hybrid (Deep Learning + ML)	Combined DenseNet201 features with various machine learning models like SVM and Random Forest for lung cancer detection.	Combining manual and automated features effectively and improving early detection of small tumors.
5	Ovarian cancer detection using optical coherence tomography and convolutional neural networks[36].	Deep Learning	Used 3D CNN and convolutional LSTM models to analyze 3D images from optical coherence tomography (OCT).	Managing noisy images and limited data, and ensuring reliable detection.
6	Automatic detection of prostate cancer grades and chronic prostatitisinbiparametric MRI[37].	Deep Learning	used a 3D nnU-Net to optimize imaging parameters and use data augmentation in order to identify prostate cancer grades and prostatetitis in MRI images.	Defining optimal imaging parameters, compensating for multimodal data shifts, and improving detection rates for clinically significant prostate cancer and prostatitis.
7	MFEUsLNet: Skin cancer detection and classification using integrated AI with multilevel feature extraction-based unsupervised learning[38].	Unsupervised Learning and deep learning	Recurrent Neural Network (RNN) model for the classification of skin cancer into seven types.	Variations in skin tones across ethnicities, Imbalanced and limited datasets.Challenges with noise and artifacts in images.

VII.CONCLUSION

Deep learning algorithms have revolutionized cancer detection, segmentation, and classification through the use of medical imaging, greatly enhancing patient care, diagnostic efficiency, and accuracy. This review examines significant advancements in the detection of malignancies, including skin, ovarian, breast, prostate, and lung cancers, while also emphasizing important obstacles. There are still important problems to be resolved, including interpretability, processing needs, model generalization, and data quality.

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The creation of reliable and understandable models, increasing the availability of data, improving generalization skills, and guaranteeing adherence to privacy and ethical standards should be the top priorities of future initiatives. The field has the potential to transform cancer diagnosis and therapy by overcoming these obstacles and making progress in these areas. This would open the door for more dependable, precise, and clinically significant solutions, which would eventually improve patient outcomes. In conclusion, this paper provides an overview of various cancer detection techniques leveraging deep learning, offering valuable insights into their methodologies and applications.

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