Deep Learning in Cancer Diagnosis

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Abstract: One of the most serious illnesses that has claimed many lives in the modern world is cancer. Most of the time, medical professionals can only identify cancer in its advanced stages. As the disease progresses, organizing treatment for cancer makes it very difficult to increase the patients likelihood of survival. Thus, early cancer detection becomes crucial for selecting the best course of action for therapy and scheduling surgery. Physicians are able to diagnose a wide range of illnesses, including cancer, with the aid of medical image analysis and interpretation, including MRI and CT scans. On the other hand, manual medical picture interpretation is expensive, time-consuming, and biased. In order to analyze and interpret medical pictures independently, practitioners are becoming more and more interested in a branch of artificial intelligence called deep learning.

Keywords: Cancer detection; convolutional neural networks (CNNs); deep learning; machine learning; Autoencoders (AEs).

1. INTRODUCTION

Cancer sufferers' lives are affected in all spheres by the cancer, including their social, familial, and professional lives. Cancer is thought to be the leading cause of death worldwide. Fighting cancer presents hurdles for both medical professionals and researchers[1]. According to predictions from the World Health Organization (WHO), there could be 27.5 million instances of cancer by 2040, which would mean 16.3 million deaths from the disease. In contrast to other diseases, however, cancer diagnosis and treatment are difficult and time-consuming tasks. Cancer arises from the regular cell division and reproduction in several organs and tissues, combined with the development of malignant neoplasms.[2]

Today cancer disease is a second most common cause of death among the diseases. Some of the well-known types of cancer that people suffer from are brain cancer, prostate cancer, leukemia, skin cancer, and breast cancer among others. It has been estimated that 13.1 million deaths worldwide will be attributable to cancer by 2030. Cancer is the leading cause of death in the world, accounting for one in ten fatalities (male and female combined). The main reason for the rise in cancer-related mortality is that the disease is often diagnosed in its later stages, making treatment more difficult. It has been noted that when cancer is discovered early on, the majority of patients receive effective treatment.

Early detection of the disease can therefore aid in appropriate therapy and increase cancer patients' chances of long-term survival.

In terms of computer-mediated cancer diagnoses, many methods have been developed recently. Regarding the purpose of diagnosing cancer, medical professionals are paying more and more attention to systems with artificial intelligence (AI) that can imitate human intellect. AI-based learning systems are frequently employed to address real-world issues. Deep learning in particular is a type of AI learning system.

Using medical imagery, deep learning systems aid medical professionals in the early detection of cancer. In order to identify comparable patterns in fresh medical images, these systems need to have their machine learning techniques trained. Based on their method of learning, deep learning systems can be classified as either supervised, semi-supervised, unsupervised, or reinforced learning.

2. Process for Cancer Detection:

The effectiveness of disease diagnosis methods and subsequently medical care has increased due to recent developments in information and medical technologies. Early disease detection is greatly aided by medical imaging techniques like CT, MRI, and ultrasound. In order to identify early stages of cancer as well tailor therapy, medical imaging is crucial.
Pre-processing, segmentation, and post-processing are the three stages involved in using deep learning systems to identify cancer from medical images in order to better analyze the images and identify cancer disease [3]. Various techniques are applied in each stage of the cancer detection process using medical images, prior to the deep learning algorithm being trained. The ensuing subsections contain the specifics.

Reducing human error.

- **Phase Pre-processing:**

  The first step in the process of using medical images to detect cancer is called pre-processing. Image quality in medicine may suffer from noise. The precision with medical picture is assessed in order to diagnose cancer may be impacted by noise. The pre-processing stage enhances the quality of raw medical images by removing noise. Images with low contrast that show skin lesions, healthy skin, asymmetrical borders, and other skin artifacts like hairs, skin lines, and black frames are made possible by the pre-processing phase.

  Pre-processing techniques include dull razor, Gaussian filter, color space conversion, automated color equalization, black frame removal procedures, non-skin masking, hair removal methods and pseudo-random filter[4].

  The preliminary processing technique aids within the analysis of the medical imaging for precise cancer disease detection. For example, grayscale pictures are created from MRI scans and then in contrast is with a smoothing function applied in order to detect brain cancer. Skull stripping can occasionally be useful in separating the tissues of the brain from the remainder of the skull. In order to diagnose lung cancer, CT scans must be converted into grayscale images, normalized, and noise-reduced. To eliminate unwanted areas, the images can be transformed into binary images.

- **Phase Image Segmentation:**

  Another important process, which is carried out during the analysis of medical image processing, is called image segmentation. To obtain the information necessary, the picture of medicine is divided into different areas or prime topics. In this step, the region of interest and the image's background are distinguished[5]. There are four categories into which techniques for dividing up medical images can be categorized, as follows:

  1. Segmentation based on models
  2. Segmentation using pixels
  3. Segmentation based on thresholds

- **Phase Post-processing**

  The post-processing stage of the pipeline for evaluation medical pictures to diagnose cancer illness entails obtaining pertinent characteristics after performing pre-processing and image segmentation procedures. Several techniques have been put forth to complete the task of grabbing features. The most popular techniques are region merging, opening and closing operations, island removal, border expansion, and smoothing. Following the application of after processing techniques, the attributes are taken out of the chosen area of the picture and further examined in order to identify the disease. Principal component analysis (PCA), wavelet packet transform (WPT), grey level co-occurrence matrix (GLCM), Gaussian derivative kernels, Fourier power spectrum (FPS), and decision boundary characteristics are some of the frequently used feature extraction techniques.[6]

- **Phase Classification:**

  Using deep learning techniques, medical image classification into cancer categories is done during the classification phase. This is done using the features that were extracted during the postprocessing phase. During the classification phase the classifier which in this case is a deep learning classifier is trained and tested to determine the various types of cancer that can be diagnosed from the images based on the features arrived at. In the first step, a deep learning classifier is initialized and practiced on the images of training dataset. According to the extracted features, the used deep learning model that has been trained predicts the type of cancer in unknown images using the right number of training iterations. Among the identification of cancer using deep learning, convolution neural networks CNNs, long short-term memory LSTM, recurrent neural networks RNNs and gated recurrent units GRUs are commonly used.
Models for Deep Learning:
Accurately identifying and diagnosing cancer disease is greatly influenced by the proper gathering and processing of medical pictures. There are numerous high-resolution image capture systems available, including CT, MRI, and X-ray scanners. Following the pre-processing stage, the illness identification system uses these medical images to extract pertinent features, which are then used to train the models. The disease can also be identified using the trained model on corresponding unidentified medical photos.

A subset of machine learning techniques known as "deep learning" allows one to train a model based on the outcome and approximate the outcome using the available data set. Neural networks containing numerous layers inside neurons, the output layer, many hidden layers, and the input layer, among others are used in deep learning techniques. Multiple layers allow for more accurate training of the deep learning model[7]. The four kinds of deep learning models of learning that is rewarded, unsupervised, semi-supervised and supervised are shown in Fig. can be distinguished by their respective learning techniques.

Convolutional Neural Networks (CNN):
Eq. (1) provides a mathematical representation of the convolutional layer.

\[ G(X) = g^{N}(g^{N-1}(...((g^{1}(X)))) \]

In this case, \( N \) denotes the number of hidden layers, \( X \) the input vector, and \( g \) the function applied to layer \( N \). According to Eq. (2), a CNN model is made up with a convolutional layer with a function \( g_{y} \) made up of many convolutional kernels \((h_{1},... h)\) that, in the \( k \)th kernel, represent a linear function[8].

\[ h_{k}(x,y) = \sum_{s=-m}^{m} \sum_{t=-n}^{n} \sum_{v=-d}^{d} V_{k}(s, t, v)X(x-s, y-t, z-v) \]

In this instance, the input pixel location is specified by \((x,y,x)\). \( X_{m} \) denotes the filter's height, \( n \) its breadth, and \( w \) its depth. The weight of the \( k \)th kernel is shown by \( V_{k} \).

CNN's pooling layer is another name for the subsampling layer. This layer uses summarized characteristics to compute the result at a particular place by summing the surrounding pixels. This layer aids in the data's feature reduction. Additionally, it demonstrates how translational and rotational transformations are invariant. For the pooling layer, numerous techniques have been put forth, such as maxpooling and average pooling[9].
**Autoencoder (AE):**

The foundation of Deep Neural Network (AE) is unsupervised learning. This network learns input data to low dimensional feature space, as seen in Fig.

The input layer, hidden layer, and output layer make up the network. There are two stages to the AE training process: encoding and decoding. The input is encoded in the first stage, as shown by Eq. 

\[ J = \sigma(Y_{i,j} + B_{i,j}) \]

In this case, \( \sigma \) stands for an activation function. As illustrated in Eq., a new weight matrix is used in the decoding of the representation \( J \).

\[ \hat{I} = \hat{\sigma}(Y_{j,i} + B_{j,i}) \] [10]

**Deep Learning Methods in Cancer Detection:**

One branch of machine learning algorithms that excels at analyzing digital images is called deep learning. Comparing deep learning techniques to traditional machine learning algorithms, recent results have shown an astounding level of accuracy. By employing multiple layered architectures, images processing techniques and manually collected features are no longer necessary thanks to deep learning models. The models are notable for their ability to extract images at a more profound degree by splitting them into two successive layers. Using various feature maps, models for deep learning allow for the analysis of various image shapes, patterns, densities, and colors. Time series analysis, image processing, and natural language processing have all benefited from the effective application of deep learning models. Additionally, deep learning has emerged as the most widely used technique for identifying various diseases from medical image analysis. Deep learning models have been effectively used by the researchers to identify various cancer types from pictures used in medicine, such as CT, MRI and ultrasound scans.

**Benefits of Cancer Detection with Deep Learning:**

- **Early Detection:** Deep learning models are capable of helping detect cancerous lesions or tumors during early stages with relative problem-solving accuracy with the aid of medical images like X-rays, MRIs and or CT scans. It has often been reported that higher survival ratios and better treatments are due to early diagnosis.
- **Increased Accuracy:** When compared to human evaluations, deep learning algorithms can frequently analyze enormous volumes of medical data and images more accurately. By doing this, the likelihood of false positives or false negatives in cancer diagnosis is decreased.
- **Speed and Efficiency:** Compared to human experts, automated deep learning systems can process and analyze medical images far more quickly, which could shorten the time needed for diagnosis. In urgent situations where prompt intervention is essential, this speed may be critical.
- **Personalized medicine:** By evaluating a patient's genetic data, medical history, and response to treatment, deep learning models can assist in creating more individualized and successful treatment regimens.
• Decreased Workload for Radiologists: These systems can help radiologists by pre-screening images, pointing out possible areas of concern, and freeing them up to concentrate more on complex cases, which will increase efficiency overall. However, they cannot replace radiologists.

• Economical Medical Care: By decreasing the need for extensive treatments in advanced stages of cancer, early detection and accurate diagnosis can result in more affordable treatments, which may lower long-term healthcare costs.

• Continuous Learning and Improvement: Over time, deep learning models’ accuracy and dependability will increase as a result of their ability to continuously learn from new cases and data.

• Healthcare Accessible: AI-powered cancer detection has the potential to improve access to high-quality care, particularly in areas with little access to specialists in medicine.

Limitations of Cancer Detection with Deep Learning:

• Quantity and Quality of Data: During the process of training deep learning models, one requires a large quality collection of data.

• Interpretability: These models are often coined black boxes because it is challenging to determine how to arrive at a specific diagnosis by the deep learning models.

• Generalization: It’s possible that models developed using particular datasets won’t translate well to other populations or imaging technologies.

• Regulatory Difficulties: The use of AI in healthcare is surrounded by legal restrictions and compliance problems.

• Expertise from Humans: Although deep learning systems can help radiologists, they cannot take the place of human expertise. Validating and interpreting the data produced by these systems requires medical specialists.

• Ethical Concerns: In healthcare AI, consent, patient privacy, and the appropriate use of patient data are critical issues.

• Infrastructure and Cost: Putting deep learning systems into place and keeping them up to date in medical settings can be costly.

• Continuous Learning and Updates: As new data becomes available or as algorithms advance, these models require ongoing retraining and updates.

Methodology for Cancer Detection using Deep Learning:

Data Preparation and Collection:

• Compile a heterogeneous dataset comprising both cancerous and non-cancerous samples from medical images (such as MRIs, CT scans, and X-rays) or genomic data (such as gene expressions and mutations).

Preprocessing:

• To guarantee consistency in format and quality, normalize and standardize the data.

Model Choice:

• Choose an architecture for deep learning depending on their application- RNNs for genomic sequences and CNNs for image data for instance.

Instruction:

• To train and assess the model, partition the dataset into test, validation, and training sets.

• Utilizing the training set, train the model and iteratively change its parameters to minimize the loss function.

Verification and Adjustment:

• Validating the model using the validation set, analyze the model’s performance and make changes to the parameters of learning such as the learning rate, batch size, etc.

Assessment:

• Utilizing the test set, evaluate the model in order to determine its performance metrics (ROC curve, accuracy, precision, recall, F1-score, etc.).

Implementation and Observation:

• Use the trained model in a research or clinical context, incorporating it into workflows or diagnostic tools.
To keep the model accurate and relevant, keep a close eye on its performance and periodically retrain it using fresh data.

Observing Regulations and Considering Ethics:
- Assure adherence to laws governing medical AI applications (such as US FDA regulations) and moral issues pertaining to patient data privacy and consent.

Cooperation and Enhancement:
- Work together with medical professionals to interpret the model's results and successfully apply it to clinical settings.
- Iteratively enhance the model in response to user feedback, fresh findings, and developments in deep learning methodologies.
Conclusions and future scope:

The use of machines to detect and treat cancer has revolutionized medical science in the last few decades. In light of this, this paper has provided a thorough analysis of contemporary methods for the diagnosis and treatment of a number of serious cancers that affect the human body. This article's main goal is to review, evaluate, classify, and identify current limitations related to various cancer types' methodologies. Six types of cancer have been presented in the review: such as skin cancer and brain tumors or lung cancer and breast cancer or liver cancer and leukemia. Besides, this paper has described four critical stages of automated cancer diagnosis, namely tumor segmentation, feature extraction, image pre-processing and classification based on benchmark datasets. In more details, the primary purpose of this study is to help those potential researchers who are willing to begin their own research in this line by providing them with adequate knowledge.

Last but not the least, proper assessment of the pros and cons of the current most effective means of machines that can help in identifying cancer cells. Thus, accuracy for each cancer category is still not at the level of maturity. In the case of testing their suggested methods most of the researchers either employed a small set or no benchmark datasets at all. To this end, it highlights the current state-of-the-art methods in use and compares and contrasts them using benchmark datasets, Students are also made to understand the limitations of the said methods.

The primary obstacles in cancer detection and treatment involve reconfiguring the research process, comprehending the mechanisms of cancer proliferation, creating preclinical models, efficiently managing intricate cancers, implementing early treatment tactics, formulating inventive methods for planning and executing clinical trials, and improving diagnostic precision to enable physicians to offer second opinions and early interventions.

REFERENCES:


