Cancer Detection and Classification Using Artificial Intelligence Techniques: A Review

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Abstract

Cancer is the umbrella term for a collection of over a hundred diseases. Cancer is a term used to describe a group of diseases that all begin when aberrant cells grow out of control. Cancer, if left untreated, can lead to major health concerns and even death. Cancer can be detected early, which can lower death and morbidity. This document provides an overview of lung, breast, and brain cancer detection approaches. Artificial intelligence techniques such as support vector machine neural networks, artificial neural networks, fuzzy logic, and adaptive neuro-fuzzy inference system are used in conjunction with medical imaging such as X-ray, ultrasound, magnetic resonance imaging, and computed tomography scan images in these diagnosis methods. The most important approach for a precise diagnosis of human cancer is to use imaging techniques. We looked into all of these methods in order to find one that can provide superior accuracy and identify the best medical images for each type of cancer.

Keywords: *Medical Imaging, Artificial Intelligence Techniques, Lung Cancer, Breast Cancer, Brain Cancer*

Introduction:

The term "cancer" refers to a collection of disorders that are all connected. Several body tissues begin to divide without stopping and spread surrounding cells in all types of cancer. Cancer can begin in practically any part of the human body, which is made up of trillions of cells. Human tissues grow and divide to generate new tissues as needed by the human body. Cells die as they age or get damaged, and are replaced by new cells. When cancer develops, however, this ordered process is disrupted. Older or ruined cells live when they should die, and new cells develop when they are not needed as cells become increasingly aberrant (Dalerba, Cho, & Clarke, 2007). These excess cells can divide indefinitely, leading to tumour formation. Solid tumours, which are made up of cell masses, are formed by a variety of malignancies. Blood cancers, such as leukaemia, may not always produce solid tumours. Cancer tumours are malignant because they can infiltrate or spread into neighbouring cells. A variety of cancer tissues from these tumours have the potential to break off and go to other parts of the body. Through the blood or lymph system, new tumours can spread to places away from the main cancer growth. Benign tumours can often be removed, and in many cases, they do not return and spread to other parts of the body. Cancer is the top cause of death in the globe. According to the International Agency for Research on Cancer's estimates, 14.1 million new cancer cases were diagnosed in 2012, and 8.2 million people died from cancer. The National Cancer Institute (NCI) published a study in 2012.

Computer-aided diagnosis (CAD) in medicine

Image categorization by hand is a difficult and time-consuming operation. Interobserver variability and human errors are very common in this activity. As a result, manual classification produces exceedingly poor critical outcomes, significantly increasing the workload of radiologists, who are in limited supply.

Furthermore, medical care costs related to imaging are constantly rising (Cheng, Cai, Chen, Hu, & Lou, 2003). As a result, new diagnostic approaches are required. CAD is one of the key research issues in diagnostic radiology and medical imaging at the moment (Murino, Puppo, Sona, Cristani, & Sansone, 2015). Medical doctors can use the CAD technique to detect diseases more quickly while reducing examination time and cost, as well as avoiding unneeded biopsy operations. With the use of computed tomography (CT), X-ray, magnetic resonance imaging (MRI), or mammography pictures, CAD is currently a more acceptable approach for initial cancer diagnosis (Doi, 2007). CAD serves as a useful link between the input images and the radiologist. Although the CAD output is not regarded a final product, it is utilised as a point of reference for further testing in the associated field. The CAD aids doctors in detecting cancer earlier and more precisely. CAD can be created in conjunction with basic components of a variety of fields, including artificial intelligence (AI), image analysis, medical information processing and management, digital image processing, and pattern recognition (Murino et al., 2015). The computer-aided design (CAD) technology is more dependable and efficient. Specificity, sensitivity, and absolute detection rate are all important factors in this system.

Artificial intelligence (AI) techniques are methods for creating and developing computer software applications. Artificial intelligence (AI) is a programme that can mimic human perception. In order to give AI with the ability to analyse or solve dilemmas, as well as the ability to categorise and identify things, this application typically involves gathering input. The support vector machine (SVM) neural network, fuzzy models, artificial neural network (ANN), and K-nearest neighbour are all described in this paper (K-NN).

Research Methodology

Researchers use a variety of sophisticated algorithms to classify and segment medical picture data in order to find anomalies in various parts of the body. This research is limited to the classification and segmentation of medical picture data using the majority of these techniques.

MEDICAL IMAGING

Over time, medical imaging has evolved into an important aspect of early cancer diagnosis, detection, and therapy. Medical imaging is frequently the first step in preventing the spread of cancer through earlier identification, and it also aids in the treatment or complete elimination of cancer in many circumstances.

CT imaging, MRI, mammography, ultrasound (US) imaging, X-ray imaging, and other imaging modalities used to combat cancer are all highlighted in this article (Fig. 1)

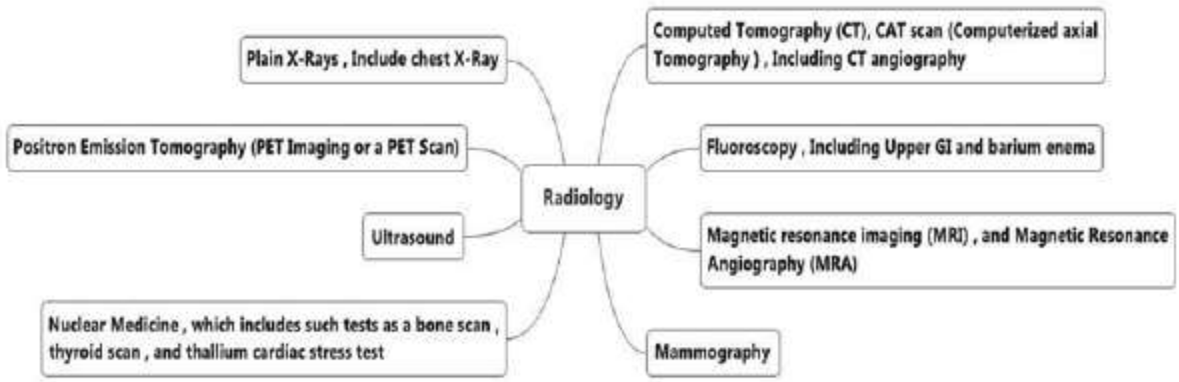

Figure 1: Various types of Medical Images

To detect and classify various forms of malignancies, various AI algorithms are applied. The accuracy of these procedures varied from year to year. This fluctuating pattern could be caused by a variety of variables, including network structure. The following selected characteristics vary while constructing architecture for specific applications: network type, number of layers, number of nodes in hidden levels, activation function between layers, and dataset size (Dhokia, Kumar, Vichare, Newman, & Allen, 2008). (Peng, Jianmin, & Wu, 2009). The ability of these networks to function with varied data and reduce performance error to the smallest amount is referred to as network generalisation.

BREAST CANCER

Breast cancer is a cancerous tumour that begins in the breast tissues. This malignancy has the potential to spread to other sections of the body or straight into nearby areas. This type of cancer affects almost primarily women, but it can also affect men (G. Schaefer et al., 2007). With current functions requiring inspections, there has been a lot of interest in using computational algorithms to help detect and diagnose breast cancer, which is one of the most common malignancies. The mammography technique in question is a basic but powerful tool for detecting breast cancer at an early stage (Cheng, Shan, Ju, Guo, & Zhang, 2010). Dr. William H. Walberg provided the Wisconsin Breast Cancer Data (WBCD) source, and the different AI techniques employed by researchers and applied to the WBCD database for prognosis, detection, and classification breast cancer are addressed in the following paragraphs. There are 699 occurrences in this database, which is easily accessible through the UCI database repository.

NEURAL NETWORKS

For the diagnosis, prognosis, prediction, and classification of breast cancer throughout time, several neural network algorithms employ both supervised and unsupervised learning techniques. LCDS (Z.-H. Zhou, Jiang, Yang, & Chen, 2002) is a lung cancer diagnosis system that uses photographs of needle biopsy specimens to identify lung cancer cells. To fulfil its purpose, this system employs neural ensemble-based detection (NED) using a two-level ensemble architecture. The NED has a high overall recognition rate and a low percentage of false negative identification, but the LCD needs to enhance its performance when dealing with cells that are overlapped. (Pereira, Alexandre, Mendonça, & Campilho, 2006) looked at a method for classifying lung nodules in X-ray chest images and radiographs. The results of the multi classifier (MLP) technique can be utilised to reduce false-positive nodules. (Nehemiah & Kannan, 2006) proposed and succeeded in detecting and classifying lung nodules into non-cancerous and malignant nodules using image processing and feedforward neural networks.

For extracting and segmenting sputum cells for early lung cancer diagnosis, Bayesian classification and the HNN algorithm (Taher, Werghi, & Al-Ahmad, 2012) were used, with an accuracy of 88.62 percent. To detect and classify lung cancer in its early stages, (Ada1, 2013) used a two-method preprocessing and a feed-forward BPNN classifier. With a success rate of 96.4 percent, the neural network was able to correctly classify the data. (Kuruvilla & Gunavathi, 2014) presented feedforward and feedforward BPNN as classification methods for detecting lung nodules in CT images. The rear-correction learning rule is used in feedforward back-propagation, which results in superior categorization. The accuracy of feedforward backpropagation was 93.3 percent, with a minimal mean square error of 0.0942. Furthermore, the skewness parameter and the training function produce the highest accuracy. An MLP was presented by (Gorynski et al., 2014) for the early identification and diagnosis of lung cancer. In detecting and classifying lung nodules, neural networks achieved a high accuracy of more than 95%.

BRAIN CANCER

The brain and spinal cord make up the central nervous system. The most common cause of cancer-related death is most likely a brain tumour. Gliomas and meningiomas are two terms for brain tumours.

Brain cancer and tumours that begin in the brain are the two most common forms of brain tumours.

Cancer cells in the brain and spinal cord can spread and invade healthy cells, although they seldom move to other parts of the body. A more prevalent type of brain tumour is a secondary brain tumour. The cancer starts in another part of the body, such as the lung or breast, and then travels to the brain. A metastatic brain tumour is the term for this type of tumour. If found early on in the disease's progression, brain cancer is typically curable and treated. Brain tumours can spread and cause death if they are not treated.

Images of the human brain are obtained using a variety of approaches. X-rays, CT scans, electroencephalogram (EEG) signals, and magnetic resonance imaging (MRI) are examples of these types of tests. These techniques are used to make diagnoses.

CONCLUSION:

Many people's lives are saved because to accurate cancer classification. Many researchers are currently interested in applying AI classification approaches to categorise cancer, despite the usage of well-known diagnostic tools. The purpose of this study was to examine the performance of AI classification techniques using cancer classification data, such as ANN methodologies, ANFIS, FL, and SVM neural networks. The methods are effective tools for categorising cancer data. Mammograms provided the highest accurate results for breast cancer, with a 99.73 percent accuracy rate using the FL simple grid classifier. PET images had a greater accuracy of 97 percent in lung cancer, which was accomplished using an SVM classifier, and CT scans had the highest accuracy of 96.04 percent, which was reached using feedforward backpropagation. The most accurate result for brain cancer was a 100 percent MRI scan, which was achieved with a PPN. Several AI algorithms can be used to diagnose malignancies with varying degrees of accuracy utilising various sources of data. For the identification and classification of breast, lung, and brain malignancies, we discovered the best classification algorithm and the best medical image type with the highest accuracy.

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