REVIEW ARTICLE

Evolution in Spinal Fracture Diagnosis and Brain Tumor Detection in the Last two Decades: A Timeline-Based Study

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Abstract

Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) are arguably the most prominent and most widely used healthcare diagnostic modalities for a wide range of applications. There are certain specific applications for which a particular modality is specifically used or has been adopted over a period of time because of reasons like good diagnostic accuracy, fast diagnosis, etc. One such application for CT has been "Spinal Fracture Diagnosis" and for MRI has been "Brain Tumor Detection". This study presents case studies from different time periods to demonstrate the evolution of these respective applications and emphasizes the role of Artificial Intelligence (AI) based techniques like machine learning, deep learning, etc. for advancements in the diagnostic process. The case studies will enable the new researchers to understand the background and the work done in the respective time period. The time period of the studies referred to is between the years 2000 and 2023 (Present date). The purpose of this study is to enlighten the reader about the evolution of spinal fractures and brain tumor diagnosis which are understood to be primary applications of CT and MRI, respectively and, encourage further study into topics pertaining to AI-based tools used in diagnostic modalities for applications like automatic detection and prediction, smart decision making, early detection, etc.

Keywords: Evolution; Computed Tomography; Magnetic Resonance Imaging; Artificial Intelligence; Deep Learning.

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1. Methodology & Approach

In this study, to demonstrate the case studies we have tried to incorporate a process-oriented approach. The approach is such that at the beginning of every case study we describe the background of the era or period we are referring to. This is followed by describing the work done in the referred case study, followed by the advancements in technology in that era, and finally an interpretation. The purpose of using this technique is to demonstrate a larger picture to the reader in terms of the progress and evolution that has happened over the past two decades. For instance, while talking about "Spinal Fractures", we referred to studies from three different time periods to demonstrate an evolution of diagnosis of spinal fractures using Computed Tomography (CT) scans as a modality over the years. The same approach has been implemented for Magnetic Resonance Imaging (MRI). The time frame this manuscript follows is between the years 2000-2023 and the present date. We aim to describe a situation and state the actions which were taken then, and how these actions determined the results of the findings alongside informing the reader about the advancements from time to time. The time interval followed between the case studies is typically 7-10 years.

2. Evolution of Diagnosis of "Spinal Fractures"

Figure 1 shows the overall evolution and progress in the field of computed tomography for the application of diagnosing spinal fractures in the last two decades. It has been observed that over more than a decade the CT scan has emerged as one of the most prominent and common diagnostic modalities used to diagnose various conditions like muscle and bone disorders like bone tumors and fractures, it is also used to monitor conditions like cancer, heart disease, lung nodules, and liver masses. Additionally, it can be used to diagnose internal bleeding or blood clots. A variety of factors like trauma, osteoporosis, or cancer can lead to spinal fractures. A CT scan has proved to be very useful in identifying the location and severity of the fracture as well as complications and injuries associated with the same.

In the early 2000s, a study by S. H. Gehlbach, *et al.* suggested that diagnosis majorly relied upon the clinician based on his understanding and interpretation. The study involves a cross-sectional survey of regional hospitals to examine the frequency with which vertebral fractures are identified and treated by clinicians in a population of hospitalized older women who have radiographic evidence of fractures. From the set of data studied, moderate or severe vertebral fractures were identified for 132 (14.1%) study subjects, but only 17 (1.8%) of the 934 participants had a discharge diagnosis of vertebral fracture [1].

The technicalities considered by the radiologists around that period (i.e. between 2000-2005) include;

a. Slice thickness: Thinner slices provided more details but typically slice thickness varied from 1-5 mm.

b. Use of Contrast Agents: For CT scans of the spine, iodine-based contrast agents were used. They helped highlight the fractures and abnormalities associated with them.

c. Use of Reconstruction algorithms like Filtered Back Projection (FBP), and post-processing software were used.

Later in the year 2010, a study by A.K. Ganiyusufoglu, *et al.* suggested the use of MRI for the diagnosis of spinal fractures. The study aimed to compare CT and MRI as diagnostic modalities for the purpose of identifying which modality gives better results for the diagnosis of spinal

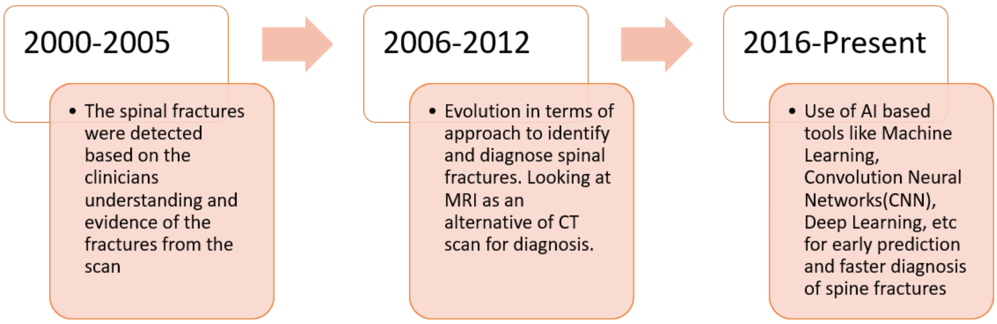

Figure 1. Evolution of "Diagnosis of Spinal Fractures using CT Scan

fractures. In the study clinical data from 57 adolescents and young adults with a diagnosis of spinal injury were reviewed. All 57 cases were checked using both 1.5T MRI and 16-section CT examination. All the MRI and CT results were reviewed and analyzed separately. The results suggested that in total, 73 complete and 32 incomplete stress fractures were detected with CT. Sixty-seven complete, 24 incomplete fractures, and eight stress reactions were detected using MRI in the same study group. The study referred to in this case concluded that MRI has similar diagnostic accuracy to CT in determining spinal fractures. Further, the study also mentions that MRI has certain limitations as compared to CT scans [2].

There were several advancements between the years 2000-2010. The technicalities considered by the radiologists around that period (i.e. between 2006-2012) include;

a. Multidetector CT (MDCT): The MDCT was developed in the early 2000s and evolved over the years. The technique allowed higher resolution images alongside faster scanning time.

b. Iterative reconstruction algorithms: The Iterative reconstruction algorithms were the major breakthrough in terms of advancements in the diagnosis of spinal fractures between the years 2006- 2012. It significantly improved the image quality and also reduced the radiation exposure.

c. Computer-aided diagnosis (CAD): CAD software assisted radiologists in detecting and diagnosing spinal fractures more accurately and efficiently.

d. Image fusion: The image fusion technique was developed in this period. It provided a more comprehensive view of the spine.

Further, with the passage of time, there were several advancements.

A recent study from the year 2022 by S. H. Kong, *et al.* suggests the prominent use of AI-based tools for diagnosis of spinal fractures. Artificial intelligence (AI)-based tools like machine learning, deep learning, and Convolution Neural Networks (CNN) are playing a key role in faster and more accurate diagnosis of spinal fractures. The work was done to suggest that a study of nearly 1600 participants aged 50-75 years was carried out at the National University Hospital in Korea. Positive and negative cases were defined according to whether vertebral fractures developed during follow-up. A CNN-based prediction algorithm was used in the process. Of the total participants, 1,188 (74.4%) were women, and the mean age was 60.5 years. During a mean follow-up period of 40.7 months, vertebral fractures occurred in 7.5% (120 / 1,595) of participants. This was successfully predicted using the respective algorithm used, which was based on DeepSurv [3].

The newest advancements and technicalities considered by radiologists since 2016- the present date are as follows;

a. AI: It has been developed for the efficient detection of spinal fractures. It can further predict and determine the severity and complications of a fracture. It is majorly used for image analysis in spinal fracture diagnosis.

b. Cone beam CT (CBCT): It is one of the newest technologies developed since 2012. It uses a cone-shaped beam to produce 3D images. This technique essentially provides images of higher resolution than traditional CT techniques.

c. 3D Printing: 3D printing is based upon the creation of physical models of the spine based on the scan data. This technique can be helpful for surgeons, especially for planning complex spinal procedures.

2.1. Interpretation

It can be inferred from the presented cases that in the early 2000s, the diagnosis heavily relied upon the radiologists' understanding. Back then, radiologists considered several technicalities such as slice thickness and the use of contrast agents. Reconstruction algorithms were being developed to help radiologists in the diagnosis process. Later from the case presented in 2010, it can be inferred that for spinal fractures radiologists were looking at alternative modalities like MRI for diagnosis purposes. Post 2005 or so, multidetector CT scanners were developed and CAD tools were also deployed for better performance. Finally, the final case from 2022 describes the present date situation where AI-based tools are leading the advancements in the field and are being used for classification, prediction, etc. [4-12].

3. Evolution of "Brain Tumor Detection"

Figure 2 summarizes the progress in brain tumor detection using MRI in the last two decades. It is well known that the magnetic resonance imaging technique is used to examine organs, tissues, and skeletal systems. It produces high-resolution images of the inside of the body that help diagnose a variety of problems. The MRI is very useful for applications like diagnosing conditions related to the brain and spinal cord like tumors. In addition, an MRI scan is also recommended for applications associated with the heart and blood vessels, to diagnose abnormalities in internal organs like the liver, kidneys, pancreas, etc. “Brain Tumour Detection” is one of the foremost applications of MRI for which MRI is the preferred first choice of equipment.

In the year 2000, a study by A. S. Capelle, *et al.* talked about unsupervised segmentation in the detection of Brain Tumors. The technicalities considered by the radiologists included factors like image resolution, image contrast, tumor shape, tumor size, location, pattern, and patient history. These basic technicalities considered by radiologists have by and large remained constant over the years. MRI was an evolving technology in the early 2000s. Basic segmentation techniques were being used in that time period. The referred study describes a method that used two parts. First, make a pre-segmentation to extract the brain from the head. Then, a second segmentation is done inside the brain. The approach revolves around unsupervised segmentation for the detection of brain tumors. The study also describes ways to obtain the brain masks and mentions the mathematics behind the segmentation process [13].

The advancements between the years 2000-2005 included;

a. Functional Magnetic Resonance Imaging (fMRI): fMRI stands for Functional MRI. It measures changes in blood flow and oxygen levels in the brain while a patient performs specific tasks.

b. Spectroscopy: Spectroscopy uses MRI to measure chemicals in the brain. This provided significant information about the tumor, its type, and its location.

c. CAD: This technology was one of the most successful and popularly used technologies of that time and is used even today with further advancements incorporated in the technology. It uses computed algorithms to analyze an MRI image It can also help radiologists differentiate between benign and malignant tumors.

In 2012, a study by A. R. Kavitha, *et al.* demonstrated the use of neural network technologies alongside advanced segmentation techniques for Brain Tumor Detection. The study further makes use of the “modified region growing” technique for detecting tumors. Modified region growth includes an orientation constraint in addition to the normal intensity constraint. The study shows that the performance of the proposed technique is systematically evaluated using the MRI brain images received from public sources. For validating the effectiveness of the modified region growth, the quantity rate parameter has been considered. For the evaluation of the proposed technique of tumor detection, the sensitivity, specificity, and accuracy values were used. Comparative analyses were made for the normal and the modified region growth using both the Feed Forward Neural Network (FFNN) and Radial Basis Function (RBF) neural network. The performance of the proposed technique is evaluated by considering the region-growing algorithm and the modified region-growing algorithm in terms of the quality rate. The tumor detection is evaluated through performance metrics namely, sensitivity, specificity, and accuracy. The results show that the modified region growth achieved better results when compared to the normal technique [14].

There were several advancements between the years 2006-2012, which shaped and further contributed to the evolution of brain tumor detection. Some of them are as follows:

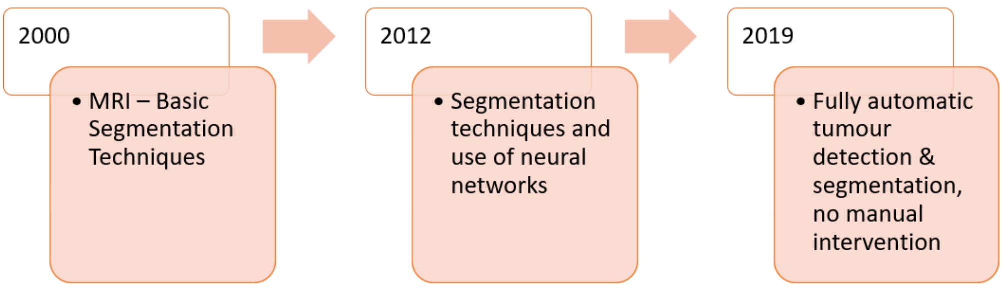

Figure 2. Evolution of "Brain Tumor Detection using MRI"

a. Dynamic Contrast-Enhanced MRI (DCE-MRI): DCE-MRI, uses contrast agents to measure the rate of blood flow and the permeability of blood vessels in the brain. It helps to differentiate between different types of brain tumors and also provides information about the intensity of the tumor

b. Magnetic Resonance Elastography (MRE): Measures the stiffness of brain tissue and helps identify tumors based on the observed abnormality

c. High-Field MRI: This technique is very useful for the detection of small tumors. It provides high resolution with strong MRI machines typically designed to have a stronger magnetic field.

d. Radiomics: It refers to an advanced use of computer algorithms for the analysis of data. It is used for the purpose of classification and prediction of brain tumors.

e. Hybrid Imaging: The combination of other imaging modalities like CT and Positron Emission Tomography (PET) for improvement in the results of detection, characterization, and prediction of brain tumors. The term 'hybrid' clearly describes the idea of using a diversified approach.

A study in 2019 by S. Tchoketch Kebir, *et al.* describes the prominent use of AI-based tools for detection and total automation of the process. The study uses the Gaussian mixture model, Fuzzy C-means, wavelet transform, and entropy segmentation methods, which all in one way or another fall under the category of AI-based tools. These are all the tools that can aid clinically and are highly useful for the purpose of segmentation. The proposed algorithm is based on two main parts: skull stripping and tumor auto-detection and segmentation. Based on the study, the results have been presented describing a performance measure-based comparison between the unsupervised methods and the proposed method used in the study, leading to the conclusion of how AI-based tools have led to more efficiency [15].

There were several advancements after 2012 to the present date, some of them are as follows;

a. Ultra-High Field MRI: This technology is one higher upgrade to the existing 'high field MRI'. These machines have magnetic fields up to 11 Tesla and can be very useful for the diagnosis of small tumors.

b. AI and Machine Learning (ML): AI and ML have probably been the most used tools by a radiologist in the present day. The AI-based algorithms have helped in diagnosing brain tumors alongside also providing information about their behavior. ML techniques have been used for analysis purposes for better patient outcome

c. Deep Learning: Deep learning is another extensively used technology under the umbrella of AI which has been highly used for predicting the intensity of brain tumors and also analyzing the MR images.

d. Non-Invasive Tumor Grading: These are advanced techniques such as multi-parametric MRI which have been used to grade brain tumors in a non-invasive manner. It has allowed for personalized treatment planning

e. Multimodal MRI: This technique refers to the integration of multiple MRI techniques for a more comprehensive assessment of brain tumors. MRI techniques such as diffusion-weighted imaging, perfusion-weighted imaging, and spectroscopy are used.

f. Radio genomics: The technique integrates imaging features with genomic data, and helps to predict the molecular analysis of the tumor, such as composition and depth.

3.1. Interpretation

It can be interpreted that, over the past two decades Brain tumor detection has seen tremendous advancements. The first case from the year 2000 describes the use of basic segmentation techniques, and the technicalities considered by the radiologists were factors like image resolution, image contrast, tumor shape, etc. The advancements in the early 2000s included fMRI and Spectroscopy. Later the case presented from the year 2012 describes the use of neural networks for diagnosis purposes, it informs about a new approach – modified region growth and techniques like feed-forward neural networks. The advancements after 2005 include the development of tools and technologies such as high-field MRI and hybrid imaging. Finally, the last case from 2019 describes the use of AI-based tools for brain tumor detection. The advancements in the present day include the usage of AI tools like machine learning and deep learning, multi-modal MRI, etc. One of the most advanced and useful developments has been that of the ultra-high field MRIs, which have proven to be very useful for the detection of small tumors [16-25].

4. Discussion

The term "Artificial Intelligence" has been a topic of extensive research and with the advancements, this term is one of the most associated terms with high-end technology today. In the field of medical imaging, with the advances in computation, diagnosis has become faster. In 2000, the technology used for spinal fracture analysis included rudimentary techniques and algorithms like the use of contrast agents and algorithms like FBP. Later computational advancements led to the development of tools like CAD. Presently, the diagnosis is majorly governed by high-end AI algorithms, deep learning, and techniques like 3D printing. Similarly, in the area of brain tumor detection back in 2000, the tools like fMRI used then could not diagnose small tumors and the computation analysis was also not as advanced as it is today. Later, high-field MRIs were introduced and with the advancements, there were technologies like multimodal MRIs which started being used alongside AI tools for better performance. There is a wide range of applications in healthcare diagnostics where AI can cause immense impact. From 2000 to 2023 AI has played a significant role in the growth of diagnostic modalities and in the improvement of healthcare delivery, patient care, and data analysis of healthcare data. Especially, after Covid-19 pandemic with the advancements in the field of CT and MRI, the image quality, coverage of details, and access to healthcare through mediums like telehealth have made the clinicians' job easy and the diagnosis has become faster and more accurate.

5. Conclusion

Collective information has been presented for prominent applications of CT and MRI in the form of case studies. "Spinal Fracture Diagnosis" and "Brain Tumor Detection" are the major focus and have been considered the areas of interest for CT and MRI. It has been observed that in the case of "Spinal Fracture Diagnosis," there have been several advancements and development of novel techniques such as Multidetector CT, CAD, Image Fusion, CBCT, and 3D printing techniques. Similarly, for "Brain Tumor Detection", several developments like fMRI, MRE, Hybrid Imaging, Non-Invasive Tumor Grading, and Multimodal MRI have been observed in the last two decades. After 2015, CT and MRI flourished through the application of AI, ML, and Deep Learning, which has been assisting the diagnosis for early detection, fast detection, post-scan analysis, etc. Hence, AI and ML are making radiologists' jobs simpler and the entire process more efficient.

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