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A Review on the use of Artificial Intelligence Techniques in Brain MRI Analysis

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Abstract

Over the past 20 years, the global research going on in Artificial Intelligence in applications in medication is a venue internationally, for medical trade and creating an energetic research community. The Artificial Intelligence in Medicine magazine has posted a massive amount. This paper gives an overview of the history of AI applications in brain MRI analysis to research its effect at the wider studies discipline and perceive demanding situations for its destiny. Analysis of numerous articles to create a taxonomy of research subject matters and results was done. The article is classed which might be posted between 2000 and 2018 with this taxonomy. Analyzed articles have excessive citations. Efforts are useful in figuring out popular studies works in AI primarily based on mind MRI analysis throughout specific issues. The biomedical prognosis was ruled by way of knowledge engineering research in its first decade, whilst gadget mastering, and records mining prevailed thereafter. Together these two topics have contributed a lot to the latest medical domain.

Keywords

Brain MRI, Image segmentation, Artificial Intelligence, Classification

1. Introduction

Magnetic Resonance Imaging is a noninvasive technique. It is used for diagnosis and detection of disease. It is used particularly for tissues, basically to analyze anatomical structure. Magnetic Resonance Imaging gives more accuracy and other modalities for detection of neurological conditions. Magnetic Resonance Imaging also offers great flexibility with the use of contrast agents. Brain Image segmentation provides segmentation of abnormal areas for the analysis of image. Magnetic Resonance Imaging is used for detection of tumors and is used for planning of neurosurgery and radiological therapy. In Magnetic Resonance Imaging electromagnetic pulse is generated thereby, hydrogen atom enters the tissue in excited state. Then in relaxed state, it generates radiofrequency pulse which is detected and converted into image. Image segmentation is the process of dividing an image into various regions such that pixels, within the region have alike characteristics. Segmentation differentiates abnormal region from normal region of Brain Magnetic resonance images. Brain Magnetic Resonance Images are used to detect tumors, abscesses, congenital abnormalities, Aneurysms, Venous malfunctions, Hemorrhage of brain and spinal cord, Subdural Hematoma, degenerative diseases, multiple sclerosis, hypoxic encephalopathy (dysfunction of the brain due to lack of oxygen, encephalomyelitis (infection of the brain or spinal cord), Hydrocephalus (fluid in the brain), Herniation (degeneration of the discs of spinal cord), helps plan surgeries of the spine. One such disease is Alzheimer's Disease which is one form of dementia.

Dementia is fast growing syndrome affecting majorly aged people. The syndrome is increasing rapidly in developing countries. There are 46.8 million people affected from dementia in 2015 and has crossed 50 million in 2017. Every year there is an increase of 7.7 million people living with dementia. It is going to reach 131.5 million in 2050. Dementia destroys brain cells causing people to lose their memory and judgement. People struggle to do daily activities. Dementia is a syndrome, not a disease. Dementia is a group of symptoms that affects mental cognitive tasks such as memory and reasoning. Dementia is an umbrella term that Alzheimer's disease can fall under. It can occur due to a variety of conditions, the most common of which is Alzheimer Disease. Alzheimer's disease occurs due to the deposition of Aβ proteins. The precise cause of Alzheimer is unknown except for few genetic differences. Alzheimer causes shrinkage of hippocampus and cerebral cortex and enlargement of ventricles in brain.

1.2. sMRI and fMRI

An MRI studies the water molecule's hydrogen nucleus. sMRI stands for structural MRI and fMRI stands for functional MRI. fMRI calculates the levels of oxygen whereas sMRI at high resolution views the tissue types and spaces.

2. Literature Survey

In 2000, Laurence Germond et. al.,[1] worked on automatic segmentation of Magnetic resonance image brain scans which was a complex task for two main reasons: First, because of the large difference in the brain structure, which allows limited use of general knowledge and, essentially to obtaining Magnetic Resonance Image, the details present in images that are difficult to process. To overcome such challenges, the authors have proposed in [1], co-operative framework which uses knowledge and information in individual systems, at the present time with multi-agent system, deformable model and an edge detector. The authors in [1] have used co-operative framework which is an adaptation of segmentation process of MRI brain scans. Realistic brain phantoms is reported for its evaluation. The result is that the constrained automatic and dynamic set of regions and edge agents perform co-operative segmentation including the specific gray levels in the image under consideration, brain structure's statistical model and general knowledge about Magnetic resonance Image brain scans. Basically, there are three stages of segmentation process. First is seeded region's specialization. Second is heterogeneous information fusion and third is action-reaction over slices. The individual systems interact having three modes of cooperation, namely, integrative, augmentative and confrontational which are used during three stages of segmentation process as discussed earlier. In front of the complexity of MRI brain scans segmentation, several approaches have been proposed [2,3,4] to combine several autonomous modules, each responsible for a part of the task.

In 2004 PJ Drew et. al.,[5] worked on artificial intelligence which is a branch of computer science and is capable of analyzing complex medical data. For predicting, treatment and diagnosis, outcome in many clinical scenarios is as a result of use of relationship in datasets. Using terms like 'artificial intelligence' and neural networks, many internet and Medline searches were done. By cross referencing articles, references were procured. Apart from clinical applications, an overview of many artificial intelligence techniques has been discussed by author in [5]. The use of many artificial techniques has been applied in almost every medical domain. The analytical tool most commonly used is Artificial Neural Network while other techniques included fuzzy expert systems, evolutionary computation and hybrid intelligent systems. Artificial intelligence techniques have the ability to be used in every domain of medicine. Clinical trials are needed before these techniques are used in clinical settings. To solve clinical problems many Artificial Intelligence techniques are present. However, Artificial Intelligence techniques have not been used proactively in medical domain. The attitude of clinicians is the main reason towards use of Artificial Intelligence techniques in decision making process. In a way which seems difficult to understand and impossible with opposite facts, there is no reluctance in accepting the bio- chemical results generated from an image produced by MRI. However, it is the duty of the researchers working in this field to produce proof that these techniques work on practicality. It is necessary, for confirmation of effectiveness of Artificial Intelligence systems in medicine, and there is a necessity to undertake arbitrary controlled studies. Thus, this explains the importance of application of Artificial Intelligence techniques in medicine in 21st century. There is no ambiguity that these techniques will improve the medical brain power in future clinicians.

In 2006, Ollivier Colliot at. al.,[6] worked which presented a general framework that brought together new restrictions in deformable models to establish spatial relations. In [6], the authors have depicted spatial relations as fuzzy subsets of the image space and implemented in the deformable model, which is used as new external force. In [6], the authors have considered three methods that are used to deduce external force from a fuzzy set which depicts spatial relations. The proposed method in [6] are utilized for segmenting subcortical brain structures from magnetic resonance images. The main variable constants are predicted to define relations using a training step. To improve the segments of structure having little contrast and poorly-defined boundaries, the spatial relations in deformable model has been brought in.

In 2007, H. Selvaraj et. al.,[7] worked on an intelligent classification technique to identify nor- mal and abnormal slices of brain Magnetic Resonance Imaging data. When a large amount of Magnetic Resonance Imaging data has to be studied, it may lead to wrong diagnosis by radiologists and physicians when physical understanding of tumor slices has to be done. For tumor detection, and to get rid of human error, an automated intelligent classification system has been considered which takes into account the importance of classification of image slices when abnormal MRI volume has been detected. In [7], the authors have proposed a classification system based on Least Square Support Vector Machine has been presented when tried for Magnetic Resonance Imaging slices. The classifier in [7] uses linear as well as non-linear radial basis function kernels. On comparing it with other classifiers like Support Vector Machines having linear and non-linear Radial Basis Function kernels, Multi-Layer Perceptron and K-nearest neighbor classifiers, it was deduced that Least Square Support Vector Machines performed better than all the other classifiers. Accuracy, specificity and sensitivity are the parameters on which performance has been tested. The results suggested that Least-Square Vector Machine gave better performance. This technique can be used in computer-aided healthcare systems and even in different pathological conditions.

In 2010, Ahmad El Dahsan et. al.,[8] presented a paper in which a hybrid technique for the classification of the magnetic resonance images (MRI) has been discussed. There are three stages in hybrid technique which includes feature extraction, dimensionality reduction and classification. Using discrete wavelet transform, features have been extracted related to first stage of Magnetic Resonance imaging. Principal Component analysis has been used to reduce features in second stage. Two classifiers have been used in classification stage. The authors in [8] have developed first classifier which is based on feed forward artificial neural network and second classifier based on k-nearest neighbor. These classifiers are used to classify image as normal image or abnormal image. A feed forward back propagation artificial neural network and K-nearest neighbor has success rate of 97% and 98% respectively. The proposed technique shows results which are effective and better than other works. The authors in [8] have developed a medical decision system that classifies image as normal image or abnormal image. The main benefit of medical decision support system is to aid the physicians in making a diagnosis without any hesitation. For k-nearest neighbor the sensitivity rate is 100% and specificity rate is 90%. Whereas for Forward Propagating-Artificial Neural Network, the sensitivity rate is 98.3% and specificity rate is 90%. The authors in [8] have discussed that Self organizing map(SOM) and Support Vector Machine have produced almost similar results. Artificial neural networks have produced worst sensitivity and specificity rates. The authors in [8] have stated that their results have been compared to other results based on T2-weighted Magnetic Resonance Imaging database. The method discussed in [8] is applicable for all types of Magnetic Resonance Images, whether its T1-weighted, T2 weighted or Proton Density images. The method proposed in [8] was developed for discrete wavelet transform, principal component analysis and feed forward back propagation artificial neural network and for method was discrete wavelet transform, principal component analysis and k-nearest neighbor. Accurate and Robust classifier can be made out of the results. The classification [8] performances of this study show the advantages of this technique rapid, easy to operate, non-invasive and inexpensive. The limitation [8] of this work is that it requires fresh training each time whenever there is an increase in image database. The future work involves study of pathological brain tissues including tumors and lesions.

In 2010, Yudong Zhang et. al.,[9] worked on a wavelet transformation method which was used in extracting features of a Magnetic Resonance Imaging. However, translational variant property in present in discrete wavelet transform which will obtain features with two images on the same topic and with small movement. In order to solve the problem, the paper extracts feature which uses Stationary Wavelet Transform instead of Discrete Wavelet Transform. The wavelet coefficients obtained via Stationary Wavelet Transform are far more superior as compared to Discrete Wavelet Transform. In addition, we applied Stationary Wavelet Transform to normal and abnormal brain classification. The results demonstrate that Stationary Wavelet Transform based classifier is more accurate than that of Discrete Wavelet Transform. In this paper the superiority of Stationary Wavelet Transform is discussed which is used to obtain features. Stationary Wavelet Transform is better when compared to discrete wavelet transform when we take into account its translational invariant property. SWT was applied to obtain normal and abnormal brain image classification. The results as obtained in [9] show that classification of brain image is efficient and accurate in normal and abnormal brain images. It is expected that SWT based features will be researched on denoising, fusion and compression.

In 2011, Yudong Zhang et. al.,[10] worked on the automated and accurate classification of Magnetic Resonance brain images work which shows importance for the analysis and interpretation of the images and many methods have been proposed regarding it. In this paper, they have presented a neural network (NN) based method to classify an Magnetic Resonance brain image as normal or abnormal. PCA or principal component analysis is used to reduce features of prior extracted features done by wavelet transform. The reduced features are then sent to a back propagation (BP) neural network which uses scaled conjugate gradient (SCG) to find the optimal weights of the neural network. In this paper authors have applied this method on 66 images (18 normal, 48 ab- normal). The calculated computation time for an image is 0.0451s and the classification accuracy achieved is 100% for both training set and test set. In [10] the authors have used a hybrid classifier which classifies both normal and abnormal images. The authors in [10] have proposed future work with underlying points as follows: First it is applied for Magnetic Resonance Images having mechanisms such as T1 weighted, diffusion weighted, and proton-density weighted. Second, the lift-up wavelet, which is an advanced wavelet transform, can be used to accelerate computation points. Third, study of multiple-class classification of Brain MRI can be done.

In 2014, Jin Liu et. al.,[11] worked on normal brain tissues which include White matter (WM), Gray matter (GM) and Cerebrospinal fluid (CSF) which have been divided from different tumor tissues such as active cells, necrotic core and edema. Due to non-invasive imaging and soft tissue contrast of Magnetic Resonance Imaging, the brain tumor segmentation techniques are attracting attention. The author in [11] states that in the span of two decades, the computer aided techniques are becoming more and more upgraded for segmentation of brain tumor which come approaching the routine applications. The motive of the authors is to provide overview of brain tumor segmentation. Firstly, a crisp introduction to brain tumor segmentation using image modalities is given. The prior processing of working and SOTA (state of the art) methods of MRI based segmentation is brought in. The results of Magnetic Resonance Imaging based brain tumor segmentation is assessed and validated.

Finally, trends are directed for brain Magnetic Resonance Imaging segmentation methods and future developments are made. The authors in [11], have provided a complete outline SOTA (state of the art) of Magnetic Resonance Imaging based brain tumor segmentation. The taking different characteristic features and taking spatial information in a local neighborhood into account, many of the brain tumor segmentation methods operate Magnetic Resonance Imaging due to the non-invasive and good soft tissue contrast of Magnetic Resonance Imaging and employ classification and clustering methods. The purpose of the methods is to provide an exploratory judgement in advance on diagnosis, tumor monitoring and therapy for clinical research. The results are good in medical image analysis for algorithms. However, there is distance in clinical applications. In most of the cases under research, the clinicians depend on manual segmentation of brain tumor, and there is deficit of interaction between clinicians and researchers. The availability of tools focuses on authentic research and is scarcely useful for clinicians. Therefore, using the tools in simple to use environments is unavoidable in the future. To enhance the clinical applications more quickly, some standard clinical protocols are being formulated. Computation time is also valid criterion, apart from accuracy and validity. The computation time lasts for few minutes. This computation time is hard to be accepted in clinical routines, over few minutes and real time segmentation is toilsome. Another important aspect for brain tumor segmentation methods is robustness. If in any case the automatic brain image segmentation fails, then clinicians will lose trust and will not use this method. As a result, robustness emerges as an important criterion for new results obtained.

The main focus of researchers is brain tumor segmentation and not feature obtainability. However, the latter seems to be important when considering variation or difference in viewing the different brain tumor grades and its types in actual applications. It would be interesting to explore how new features are used to obtain enhanced results. This can improve the accuracy, validity, and robustness of Magnetic Resonance Imaging-based brain tumor segmentation. The brain image segmentation will undoubtedly improve in near future and will continue to enhance itself. Magnetic Resonance Imaging techniques like Magnetic Resonance Spectroscopy known as MRS and other techniques like Perfusion Imaging (PI) and Diffusion Tensor Imaging are used. For example, a group called Section of Biomedical Image Analysis (SBIA) has worked on these modalities for over 15 years. For localization of areas brain tumor, these modalities can be used. To segment brain tumor from normal tissues, Perfusion Imaging data, Magnetic Resonance Spectroscopy data and Diffusion tensor Imaging TI data can be used. Brain tumor segmentation provides better anticipated data and helps making full use of treatment options.

In 2014, A. El-Dahshan et. al.,[12] worked that computer-aided detection/diagnosis (CAD) systems can enhance the diagnostic capabilities of physicians and reduce the time required for accurate diagnosis. The main purpose of the paper is to review segmentation and classification techniques and SOTA for the brain MRI. The authors in [12] have stated why Computer Aided Detection systems of human brain can still pose a problem. The paper proposes a hybrid intelligent machine learning technique using Computer Aided Detection through which segmentation of brain tumor can be done using Magnetic Resonance Imaging. The authors in [12] have used feed- back-pulse coupled neural-network for segmentation, Discrete Wavelet Transform is used for feature extraction, Principal component analysis for dimensionality reduction of wavelet coefficients feed forward back propagation neural network for classifying normal image and abnormal image. The proposed method in [12] uses 14 normal and 87 abnormal brain Magnetic Resonance Imaging dataset. The classification accuracy achieved is 99%. When compared to other techniques, it is much more effective. The results show that it is more robust, accurate and fast. As computational intelligence and machine learning techniques have progressed, Computer Aided Diagnosis is a better technique used. It has become one major technique used in radiology and research. In [12], the papers used in this study ranges in between 2006 to 2012.For detecting the region of interest and image segmentation, the proposed network uses feedback pulse coupled net- work, and then applies Discrete wavelet Transform for extraction of features. Third, Principal Component Analysis is applied to reduce dimensionality and find out more accurate classifier. Lastly, the reduced features are then sent to back propagation feed forward network to classify image as normal or abnormal. Robustness of the technique used is primary parameter for assessment. The authors in [12] have realized a large number of algorithms and compared it with the proposed method. According to the results, this methodology is more efficient. The authors in [12] have taken out accuracy of 99%, specificity as 92% and sensitivity as 100%. The proposed method in [12] shows that the methodology used improves the diagnosis and differentiates between normal and abnormal images using a classifier. On comparing with other methods, the used method in [12] is efficient and robust. The motive is to obtain generalized Computer Aided Diagnosis systems, without taking into account database size and quality. Therefore, Computer Aided Diagnosis system poses a problem. There are several directions which will enhance Computer Aided Diagnosis systems:1) Getting images from different institutions 2) Enhancing classification accuracy and extracting features 3) There is scope for other researchers to utilize machine learning and use it in hybrid structure 4) Further studies are required to prove that it can be used for non-specific applications.

In 2015, Andrez Larozza et. al.,[13] worked to develop a classification model using texture features and SVM (support vector machine) in contrast-enhanced T1- weighted images to differentiate between brain metastasis and radiation necrosis. 115 lesions were used to obtain texture features. 32 radiation necrosis were diagnosed. A total of 179 features were extracted six texture analysis method, 60 untreated metastases, and 23 as radiation treated metastasis. To obtain a subset of features that provided optimum performance which was a feature selection technique based on SVM (support vector machine). With a subset of seven features, when the classifier was trained with untreated metastasis and tested on treated ones, the highest classification accuracy which was evaluated over test sets was achieved with a subset of ten features when the untreated metastasis was considered. Receiver operating characteristics was obtained by considering area under the curve having mean of 0.94 and S.D of 0.07 and 0.93 mean and S.D of 0.02. It was concluded that to differentiate between radiation necrosis and brain metastasis, a high classification accuracy (AUC > 0.9) was achieved using texture features and Support Vector Machine classifier in a method based on conventional Magnetic Resonance Imaging.

In 2015, Muhammad Nazir et. al., [14] worked such that there are many approaches for accurate and automatic classification of brain Magnetic Resonance Imaging. In [14], a proposed method for detection and classification is done. Malignant and benign brain Magnetic Resonance Imaging classification has been used by ANN (artificial neural network). The three stages in brain segmentation are pre-processing, feature extraction and Classification. In removing noise, filters are used in pre-processing stage. When dealing with feature extraction color moments are extracted from MRI and color moments obtained and given to feed forward Artificial Neural Network in order to classify the image. The method applied in [14] utilized 70 images in totality. Out of which 25 were normal images and 45 abnormal images. In [14] the authors have achieved accuracy of 88.9% for training data with overall accuracy of 91.8% was achieved. The accuracy achieved for validation data was 94.9% and 94.2 % for testing data. Digital Image Processing is used for classification of image into normal and abnormal. Considering the literature, it was inferred that different authors have used different techniques in different problems. To remove the noise in Magnetic Resonance Imaging, median filter has been used. For considering main features for classification color moments are considered for feature extraction. Artificial Neural Network has been used for classifying image into normal or abnormal image. To classify the image into normal and abnormal image a binary classifier has been used. For future scope, multi-class classification is required to identify different diseases present in human brain.

In 2017, M. Angulakshmi et. al.,[15] have worked on the automatic segmentation of brain tumor is the process of separating abnormal tissues from normal tissues, such as white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF). Due to the variability in shape, size and location, the process of segmentation needs a lot of effort. Magnetic Resonance Im- ages, Positron Emission Tomography and Computer Tomography images are used to get elaborated information, psychological process and metabolic process information. For accurate brain tumor segmentation, the required information is combined using multimodal imaging techniques. Using imaging techniques like Positron Emission Technique, Magnetic Resonance Imaging, multimodal imaging and Computer Tomography, an overview of brain tumor segmentation techniques is given in [15]. The authors in [15] have discussed methods, techniques, working principle, advantages, limitations and future challenges. The methods, advantages, their limitations, and future challenges are discussed to provide insight into various techniques.

Due to the good soft tissue contrast and non-invasiveness of Magnetic Resonance Imaging, Magnetic Resonance Imaging based tumor segmentation methods have been applied more to segment brain tumor image. However, due to lack of communication and co-ordination between developers and physicians, the application of brain tumor image segmentation techniques is very low. In real time applications, technically sound algorithms are difficult to be used. Although there are many techniques for brain tumor image segmentation, manual segmentation is used for routine life. The authors in [15] have stated that due to lack of definability and easiness of tool handling, clinicians do not prefer automatic brain segmentation techniques. Therefore, easier to use tools should be referred by clinicians. The authors in [15] have stated that clinical applicability is affected due to failing systems even for lesser number of times. As, a result robustness and accuracy should be considered while using automated system. In tumor assessment, tumor volume estimation, tumor progression estimation and classification will help in achieving the goal. The brain tumor segmentation has a wider scope of research.

In 2018, Yanqing Zhang and Jyoti Islam, [16] worked on, Alzheimer disease, which is a non-curable, progressive neurological brain disorder. Earliest detection of Alzheimer's disease can be used to properly treat and prevent brain tissue damage. For the diagnosis of AD (Alzheimer's disease), many statistical and machine learning models have been used by researchers. For detection of Alzheimer's Disease, analysis of brain MRIs have been done in clinical study. Due to the alikeness in the Alzheimer's Disease Magnetic Resonance Imaging data and aged people's standard Magnetic Resonance Images, Alzheimer's disease detection is difficult. In recent times, advanced deep learning techniques have been used successfully to show human-level performance in varied fields which includes medical image analysis. The authors have proposed in [16], a deep convolutional neural network (CNN) for Alzheimer's disease diagnosis using analysis of Magnetic Resonance Imaging data. However, most of the existing methods are using binary-classification, the model discussed in [16] is used to recognize Alzheimer's Disease at different levels and has better performance for detecting Alzheimer's Disease at early stages. The authors conducted experiments which showed better results on comparison to other methods. The authors in [16] have demonstrated a competent approach for Alzheimer's Disease diagnosis using brain Magnetic Resonance Imaging dataset obtained from OASIS. While most of the work focuses on binary classification, authors in [16] have shown considerable improvement in multi-class classification. The pro- posed method in [16] can be very useful for diagnosis of Alzheimer's Disease at early stage. The method proposed in [16] has been focused on AD and can be used in other domains and the proposed approach can be used in applying Convolutional Neural Network into other areas with a limited dataset. The authors plan to use the proposed model for different Alzheimer's Disease datasets and other diagnosis of diseases.

In 2018, Muhammad Febrian Rachmadi et. al., [17], worked on a version of a convolutional neural community (CNN) scheme proposed for segmenting brain lesions with significant mass-effect, to section white count number hyperintensities (WMH) characteristic of brains without any or moderate vascular pathology in recurring medical mind magnetic resonance photo (MRI). This is a as an alternative difficult segmentation trouble due to the small area (i.e., volume) of the White Count number hypersensitivities and their similarity to non-pathological mind tissue. The authors in [17] check out the effectiveness of the 2D Convolutional Neural Network scheme by way of evaluating its performance in opposition to the ones received from some other deep studying technique: Deep Boltzmann Machine (DBM), two conventional devices getting to know strategies: Support Vector Machine (SVM) and Random Forest (RF), and a public toolbox: Lesion Segmentation Tool (LST), all said to be beneficial for segmenting White count number hypersensitivities Magnetic Resonance Imaging. The authors in [17] additionally introduce a manner to include spatial statistics in convolution degree of Convolutional Neural Network for White count number hypersensitivities segmentation named worldwide spatial statistics (Geographical Survey Information). Analysis of covariance corroborated recognized associations between WMH progression, as assessed by using all methods evaluated, and demographic and medical facts. Deep gaining knowledge of algorithms outperform conventional gadget mastering algorithms by means of apart from MRI artefacts and pathologies that seem much like White count number hypersensitivities. The proposed approach of incorporating Geographical Survey Information (GSI) additionally correctly helped Convolutional

Neural Network to gain higher computerized White count number hypersensitivities (WMH) segmentation no matter community's settings examined. This imply Dice Similarity Coefficient (DSC) values for Lesion Segmentation Tool-Lesion Growth Algorithm, Support Vector Machine, Random Forest, Deep Boltzmann Machine, Convolutional Neural Network and Convolutional Neural Network-Geographical Survey Information (GSI) were 0.2963, 0.1194, 0.1633, 0.3264, 0.5359 and 5389, respectively.

In 2019, Joe Bernal et. al.,[18] worked the best performance in a myriad of computer vision problems such as visual object recognition, detection and segmentation is done by deep convolution neural networks or Convolutional Neural Networks. The authors in [18] have stated that deep convolutional neural networks are also used for analyzing medical image which includes lesion segmentation, anatomical segmentation and classification. The paper mentioned in [18] focuses on architectures, preprocessing, data-preparation and post-processing strategies. There are three facets of the study. First facet is that how architecture has been developed or evolved itself considering State of Art (SOTA), examining the advantages and disadvantages and convert the results into datasets. Secondly, this paper gives research carried out in deep convolutional neural networks. Finally, it gives future scope of deep convolutional neural network. The proposed method was applied to Multiple Sclerosis (MS) lesion segmentation, brain tumor segmentation and structural segmentation. Although,[18] there are public datasets available for these applications, researchers still prefer to work on their databases. The limitation of public dataset is the number of training samples. Small dataset will affect the performance of deep convolutional neural networks and will restrict the capacity of algorithms. The measurements on which evaluation is done is by pixel-wise or volume-wise basis. For a better evaluation, more than one observer may be involved. In the literature reviewed, there are many parameters on which evaluation is done. Concerning the brain tumor segmentation and Multiple Sclerosis (MS) lesion, different parameters are there on which evaluation is made, such as Differential Scanning Calorimeter (DSC), precision, recall, true positive rate (TPR) and positive predictive value (PPV), absolute volume difference, lesion-wise true positive rate (LTPR) and the lesion-wise false positive rate (LFPR) are also used. Similarly, for brain tumor [18] and structure segmentation applications, the Differential Scanning Calorimeter (DSC) score, precision, and recall are among the widely used measurements. The reason behind these parameters is the challenge it poses to organizers. Convolutional neural networks (CNNs), an outstanding branch of deep learning applications to visual purposes, have earned major attention in the last years due to its breakthrough performances in varied computer vision applications, such as in object recognition, detection and segmentation challenges [19,20,21], in which they have achieved astonishing performances [22,23,24,25,26].

In 2019, Anjali Wadhwa et. al.,[27] worked that the process of segmenting tumor from MRI image of a brain is one of the highly focused areas in the community of medical science as MRI is noninvasive imaging. The paper high- lights the literature review which discusses the methods involved in brain tumor segmentation and brain imaging. The paper discusses the state-of-Art methods and quantitative end performance of state-of art methods. Contribution of various authors and different methods of image segmentation has been discussed. In the paper, it is stated that an effort has been made for researchers to explore new areas of research and it has been observed that there are other effective methods to segment brain tumor, which includes conditional random fields (CRF) with convolutional neural network (CNN) or Conditional Random fields with Deep Medic ensemble. The paper discusses exhaustive methods for image segmentation. For accurate diagnosis of tumor, the clinicians not only set new directions of research but also quantitative analysis having different parameters help readers among different state of art methods. It has widespread applications in medical science, for example, tissue classification, localization of tumors, tumor volume estimation, delineation of blood cells, surgical planning, atlas matching, and image registration [28]. Mathematical algorithms of feature extraction, modeling and measurement can be exploited in the images to detect pathology, an evolution of the disease, or to compare a normal subject to an abnormal one [29]. The accurate and reproducible quantification and morphology of tumors are of crucial importance for diagnosis, treatment planning as well as monitoring of response to oncologic therapy for brain tumors [30]. Brain tumor segmentation consists of separating different tumor tissues (active tumor, edema and necrosis) from normal brain tissues: Gray Matter, White Matter, and Cerebrospinal Fluid [31].

In 2019, Teudoro Martin Noguerol et. al [32] have worked on artificial intelligence and machine learning which has become an actuality in medical practice. In the last century many artificial intelligence techniques have been used which includes algorithms used for diagnosis and image processing and image postprocessing. The authors in [32] have stated that artificial intelligence has taken place of radiologists and have created imaging workflows. The artificial intelligence techniques have its own pros and cons which creates an obstacle in clinical domain. The paper discussed in [32] has reviewed artificial intelligence methods and a SWOT analysis (Strength Weakness Opportunities Threats) has been done in the paper.

In 2019, Siyuan Lu et. al., [33] worked to automatically detect pathological brain in magnetic resonance images (MRI) based on deep learning structure and transfer learning. Deep learning is now the trending topic in both, academics and industry. To train the entire deep learning structure, usually, the volume of Brain MRI datasets is small. Overfitting is a problem which is faced in training. Therefore, transfer learning was introduced to train the deep neural network. First, AlexNet structure was obtained. Then, the last three-layer parameters were replaced with weights and rest of the parameters were treated as initial values. Finally, MRI dataset was used to train the model.100% accuracy was achieved. The authors have proposed a method for pathological brain detection using AlexNet and transfer learning. Out-performing five SOTA (state of the art), 100% accuracy was achieved. AlexNet was restrained by transfer learning which reduced time to retrain it. The proposed method in [33] was used by doctors in clinical diagnosis. The authors in [33], have proposed a novel method which classifies a sample as normal or pathological, moreover, multi-class classification is to be developed to detect some specific-brain diseases. The use of pathological brains plays an important role for medical treatment, which remains unknown with the author's method. The future scope discussed in this paper is that the authors intend to use more MRI dataset for their proposed method and use other advanced deep learning structures for pathological brain detection.

In 2019, Muhammad Owais et. al., [34], worked on medical-picture-primarily based prognosis which is a tedious task, and small lesions in numerous medical snap shots may be disregarded with the aid of medical examiners due to the restricted attention span of the human visible device, which could adversely affect clinical treatment. However, this problem can be resolved by using exploring comparable cases inside the preceding medical database via an efficient content-based clinical photo retrieval (CBMIR) gadget. The authors in [34] have stated that in the past few years, heterogeneous scientific imaging databases have been developing hastily with the advent of various forms of medical imaging modalities. Recently, a scientific medical doctor normally refers to diverse styles of imaging modalities all collectively along with computed tomography (CT), magnetic resonance imaging (MRI), X-ray, and ultrasound, and so on of diverse organs so as for the diagnosis and treatment of precise sickness. Accurate category and retrieval of multimodal medical imaging facts is the important thing assignment for the CBMIR machine. Most preceding attempts use handmade features for scientific photo class and retrieval, which show low overall performance for a huge collection of multimodal databases. Although there are a few previous studies on the usage of deep features for classification, the wide variety of training is very small. To clear up this hassle, we advocate the classification primarily based retrieval device of the multimodal clinical images from numerous styles of imaging modalities by the use of the method of synthetic intelligence, named as a more suitable residual network (ResNet). Experimental results with 12 databases such as 50 lessons display that the accuracy and F1. Rating by our method is respectively 81.51 % and 82.52% which are higher than the ones by the previous method of content-based clinical photo retrieval (CBMIR) (the accuracy of 69.71% and F1. Rating of69.63%).

In 2019, Shigao Huang et. al., [35], This research work is done to pick out the highest quality diagnosis index for brain metastases by using system getting to know 700 cancer patients with brain metastases have been enrolled and divided into 446 schooling and 254 checking out cohorts. Seven functions and seven prediction techniques had been decided on to evaluate the performance of most cancers' diagnosis for every patient. The authors in [35] have used mutual information and tough set with particle swarm optimization (MIRSPSO) techniques to are expecting affected person's analysis with then best accuracy at vicinity under the curve (AUC) = 0.978 with deviation of 0.06. The development by means of mutual information and tough set with particle swarm optimization (MIRSPSO) in terms of AUC became at 1.72%, 1.29%, and 1.83% higher than that of the conventional statistical technique, sequential function choice (SFS), mutual statistics with particle swarm optimization (MIPSO), and mutual facts with sequential feature choice (MISFS), respectively. Furthermore, the medical performance of the great diagnosis became superior to standard statistic method in accuracy, sensitivity, and specificity. In end, identifying gold standard machine-learning techniques for the prediction of normal survival in brain metastases is critical for scientific programs. The accuracy rate by gadget-getting to know is some distance higher than that of conventional statistic methods. The prognosis for patients with brain metastases (BM) is known to be poor, as BM is one of the deadliest among various types of cancers [36,37,38,39].

In 2019, Jens Kleesiek et. al., [40], worked on Gadolinium primarily based contrast retailers (GBCAs) which have turn out to be an essential component in each day clinical choice making in the final 3 many years. However, there is an extensive consensus that Gadolinium primarily based contrast retailers (GBCAs) need to be exclusively used if no assessment-unfastened magnetic resonance imaging (MRI) technique is available to lessen the amount of implemented Gadolinium primarily based contrast retailers in sufferers. In the current take a look at, we inspect the opportunity of predicting evaluation enhancement from non-contrast multiparametric mind MRI scans the use of a deep-mastering (DL) structure.

In 2019, Mahmoud Mostapha et. al.,[41], worked on deep gaining knowledge of algorithms and in particular convolutional networks have shown first-rate fulfilment in medical picture evaluation packages, although highly few techniques have been implemented to toddler Magnetic Resonance Imaging statistics due several inherent demanding situations such as in-homogenous tissue appearance throughout the photograph, big photo intensity variability throughout the first year of existence, and a low signal to noise placing. It gives strategies addressing those demanding situations in two selected applications, mainly little one brain tissue seg- mentation at the isointense degree and pre-symptomatic disorder prediction in neurodevelopmental disorders. Corresponding techniques are reviewed, and as compared, and open troubles are recognized, particularly low information length re- strictions, elegance imbalance issues, and shortage of interpretation of the resulting deep mastering answers. The authors in [41] talk how present solutions can be adapted to approach those issues in addition to how generative models appear to be a in particular robust contender to address them.

In 2020, Andreas M. Rauschecker et. al., [42] worked on artificial intelligence (AI) shows promise across many aspects of radiology, the use of Artificial Intelligence to create differential diagnoses for rare and common diseases at brain Magnetic Resonance Imaging has not been demonstrated. To evaluate an Artificial Intelligence system for generation of differential diagnoses at brain Magnetic Resonance Imaging compared with radiologists as stated in [42]. As published in this paper, between January 2008 and January 2018, for probabilistic diagnosis, this study tested performance of 19 common and rare diagnosis. The Artificial Intelligence system uses methodologies, which includes deep learning and Bayesian networks. Deep learning was detected in first lesion. Atlas based co-registration and segmentation was used to extract 18 quantitative imaging features. Using Bayesian inference, which is used to develop differential diagnosis, the image features were combined with five clinical features. Tuning on a training set of 86 patients whose mean age 49 with 16 S.D and 53 women were done by quantitative feature extraction algorithms and conditional probabilities. Accuracy was compared with radiology res- idents, general radiologists, neuroradiology fellows, and academic neuroradiologists by using accuracy of top one, top two, and top three differential diagnoses in 92 independent test set patients as demonstrated in [42]. It was concluded that the Artificial Intelligence system in [42] approached overall top one, top two, top three differential diagnosis accuracy of neuroradiologists and exceeded that of less-specialized radiologists. Artificial intelligence (AI) shows great potential for transforming health care and medical imaging, with deep learning being the Artificial Intelligence tool with the most impact [43,44].

In 2020, Muhammad Waqas Nadeem et. al., [45], worked on Deep Learning (DL) algorithms enabled computational models encompass a couple of processing layers that constitute information with more than one tiers of abstraction. In latest years, utilization of deep learning is unexpectedly proliferating in nearly every area, especially in medical photograph processing, medical photograph evaluation, and bioinformatics. Consequently, deep getting to know has dramatically changed and stepped forward the way of reputation, prediction, and diagnosis selectively in several areas of healthcare consisting of pathology, brain tumor, lung most cancers, stomach, cardiac, and retina. Considering the extensive range of programs of deep studying, the goal of this newsletter is to check primary deep studying standards pertaining to mind tumor evaluation (e.g., segmentation, type, prediction, assessment.). An assessment carried out by means of summarizing a massive range of medical contributions to the sphere (i.e., deep getting to know in brain tumor evaluation) is offered in this examine. In [45], a coherent taxonomy of research panorama from the literature has also been mapped, and the essential components of this rising field had been discussed and analyzed. A crucial dialogue phase to reveal the constraints of deep mastering techniques has been covered on the quit to elaborate open studies demanding situations and guidelines for destiny paintings in this emergent place. There is a number of medical domains where e-health care systems are beneficial [46]. Different medical imaging techniques and methods that include X-ray, Magnetic Resonance Imaging (MRIs), Ultrasound, and Computed Tomography (CT), have a great influence on the diagnosis and treatment process of patients [47,48].

In 2020, Lilia Lazli et. al., [49], worked on Computer-aided diagnostic (CAD) structures which use gadget learning strategies that offer a synergistic impact among the neuroradiologist and the computer, permitting an efficient and rapid analysis of the patient's situation. As a part of the early analysis of Alzheimer's ailment (AD), that is a prime public fitness hassle, the Computer Aided Diagnosis gadget affords a neuro- psychological evaluation that helps mitigate its results. The use of records fusion strategies by way of Computer Aided Diagnostics structures has validated to be beneficial, they allow for the merging of data regarding the mind and its tissues from Magnetic Resonance Imaging, with that of different varieties of modalities. This multimodal fusion refines the great of brain photographs by way of decreasing redundancy and randomness, which contributes to enhancing the scientific reliability of the prognosis as compared to the use of a single modality. The purpose of this text is first to determine the main steps of the Computer Aided Diagnosis gadget for brain magnetic resonance imaging (MRI). Then to bring collectively some studies paintings related to the diagnosis of brain disorders, emphasizing Alzheimer's Disease. Thus, the maximum used strategies inside the tiers of class and brain regions segmentation are defined, highlighting their blessings and disadvantages. Secondly, on the basis of the raised problem, we advise an answer inside the framework of multimodal fusion. In this context, primarily based on quantitative size parameters, a performance takes a look at of multimodal Computer Aided Diagnosis systems is proposed by using evaluating their effectiveness with the ones exploiting a single Magnetic Resonance Imaging modality. In this situation, advances in information fusion techniques in scientific imagery are accentuated, highlighting their benefits and downsides. The contribution of multimodal fusion and the interest of hybrid fashions are sooner or later addressed, as well as the primary clinical assertions made, inside the subject of mind disease diagnosis. The paper discusses about Alzheimer's disease which is a form of dementia. It gradually deteriorates cognitive and behavioral capacities and the causes of this disease remain un- known [50].

3. Discussion

The above literature survey discusses the pros and cons as well as application and use as to where the techniques can be used and in which domain. Brain segmentation basically discusses how it can be used to classify abnormal and normal images. Most of the work has been done in medical domain and is used for diagnosis and eradication of diseases. The main findings of Literature Survey is that Discrete wavelet transform is the best method as image can be viewed in multiple resolutions and has higher accuracy and low complexity.

Brain segmentation of MRI image has been used for pathological detection of diseases which includes tumor, glioma, Adem, Adreno leukodystrophy, Cad Asil, CNS Lymphoma, HIV encephalopathy, Metastases, Migraine, MS active, MS inactive, MS Tumefactive, NMO, PRES, PML, Small Vessel Ischemic Disease, Susac Syndrome, and many other diseases like Toxic encephalopathy, Vascular Ischemia which are all diseases of the brain. The above literature Survey discusses how brain segmentation of MRI image has been used for many diseases. Some of the work done earlier only aimed at brain segmentation of MRI image. However, the shift from segmentation to use in clinical diagnosis has evolved through many years resulting in detection of brain diseases. The below Table 1 in section 3.1 shows techniques and their applications. The table has been constructed by me [51,52,53,54,55]. Thus, on analyzing the above papers we know that above techniques can be wearables. A lot has been done and a lot has to be done in this regard.

Table 1. Table defining application of Artificial Intelligence Techniques

SNO	Year	Publication	Technique	Application	Result
1	2000	Elsevier J	Edge Detection and deformable model	Brain MRI segmentation	Detection percentage, quality percentage, adequacy [1]
2	2004	R College J Review	ANN Fuzzy GA	Medicine	Theoretical [5]
3	2006	Elsevier	Fuzzy, deformable model	Brain MRI segmentation	Mean distance and similarity index [6]
4	2007	ICMED	SBM	Classification	Sensitivity, specificity, accuracy [7]
5	2010 A	World Science J	DWT, SWT	Feature extraction and Brain MRI classification	Conclusion matrix [9]
6	2010 B	Elsevier	DWT, PCA, K-NN, FP-ANN	Brain MRI segmentation	Classification, Accuracy, TP, TN, FP, FN [8]
7	2011	Elsevier	ANN, DWT, PCA	Disease diagnosis	Accuracy, variance [10]
8	2014 A	IEEE explore	survey	Tumor segmentation	Theoretical [11]
9	2014 B	Elsevier	Survey, ANN	Brain Tumor	Accuracy, sensitivity, specificity [12]
10	2015 A	IOS	ANN	Classification/segmentation	Accuracy [14]
11	2015 B	Wiley	SVM	classification	Sensitivity, specificity, AUC [13]
12	2017	IJIST	Survey	Brain tumor segmentation	Theoretical [15]
13	2018 A	IEEE explore	Ensemble CNN	Alzheimer disease	Accuracy [16]
14	2018 B	Elsevier	CNN	Brain image segmentation	Precision, recall, DSC, TP [17]
15	2019 A	Elsevier	Deep learning Alex Net	Pathological Brain Detection	Classification Accuracy [33]
16	2019 B	Elsevier	FCNN, CRF, Deep medic Ensemble	Brain tumor segmentation	Classification, Time, Dimension, Dice, Precision, Sensitivity [27]
17	2019 C	Investigative Radiology	Deep Learning architecture	Virtual contrast enhancement of Brain MRI	Classification, PSNR, AUC, SSIM, Specificity [40]
18	2019	Elsevier	Deep CNN	Brain image segmentation	Survey [18]

	D				
19	2019 E	MDPI	CBMIR	Image segmentation	Accuracy, F1 score [34]
20	2019 F	MDPI	MIRSPSO	Brain image segmentation	Prognosis Index [35]
21	2019 G	Elsevier	Deep learning	Brain image segmentation	Classification, SNR[41]
22	2019 H	ACR	SWOT	Artificial Intelligence and ML	Theoretical [32]
23	2020 A	MDPI	Deep Learning	Brain tumor segmentation	Classification [45]
24	2020 B	MDPI	CAD	Brain image segmentation	Classification [49]
25	2020 C	RSNA	AI	Brain MRI	Accuracy [42]

4. Conclusion

There has been a prime shift from know-how-based totally to statistics-driven strategies even as the interest for other studies topics including uncertainty control, image and signal processing, and other data processing has been strong since the early 1990s. With the advancement of science, humans have been eradicating diseases with the advent and evolution of technology. The longevity of life is the basis for sustenance of human population. In order to live disease free life, many scientific discoveries have been made. One such disease or rather a syndrome affecting older population is dementia. Dementia is found in older population where brain reduces in size. Different MRI techniques have been used for clinical study of brain. In order to detect dementia sMRI and fMRI is used. The review article aims to find out the best use of technique among dataset pre-processing and brain imaging through artificial intelligence which is in clinical domain and detection of normal and abnormal dementia. Dataset can be obtained for the subject from OASIS and appropriate implementation technology has to be determined and dataset of the same subject taken periodically over n number of years is required to reach the desired objective.

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