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Research Paper

DEEP LEARNING APPLICATIONS IN MEDICAL IMAGE ANALYSIS-BRAIN TUMOR

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ABSTRACT
Brain tumors are among the most critical neurological disorders, requiring early and accurate diagnosis to improve patient survival rates and treatment outcomes. Medical imaging techniques such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and Positron Emission Tomography (PET) play a vital role in detecting and analyzing brain tumors. However, manual interpretation of medical images is time-consuming and highly dependent on the expertise of radiologists. Recent advancements in deep learning have significantly enhanced the automation and accuracy of medical image analysis. This paper explores deep learning applications in brain tumor analysis using medical imaging data. The proposed framework employs deep neural networks, particularly Convolutional Neural Networks (CNNs), for image preprocessing, feature extraction, tumor segmentation, classification, and detection. Deep learning models automatically learn complex patterns from medical images, enabling precise identification of tumor regions and differentiation between tumor types. Experimental analysis demonstrates that deep learning-based approaches achieve superior accuracy, sensitivity, and reliability compared to traditional image analysis methods. The proposed framework provides an intelligent and efficient solution for supporting radiologists in brain tumor diagnosis and clinical decision-making.

I. INTRODUCTION

Machine learning algorithms have the potential to be invested deeply in all fields of medicine, from drug discovery to clinical decision making, significantly altering the way medicine is practiced. The success of machine learning algorithms at computer vision tasks in recent years comes at an opportune time when medical records are increasingly digitalized. The use of electronic health records (EHR) quadrupled from 11.8% to 39.6% amongst office-based physicians in the US from 2007 to 2012 [1]. Medical images are an integral part of a patient's EHR and are currently analyzed by human radiologists, who are limited by speed, fatigue, and experience. It takes years and great financial cost to train a qualified radiologist, and some health-care systems outsource radiology reporting to lower-cost countries such as India via tele-radiology. A delayed or erroneous diagnosis causes harm to the patient. Therefore, it is ideal for medical image analysis to be carried out by an automated, accurate and efficient machine learning algorithm. Medical image analysis is an active field of research for machine learning, partly because the data is relatively structured and labelled, and it is likely that this will be the area where patients first interact with functioning, practical artificial intelligence systems. This is significant for two reasons. Firstly, in terms of actual patient metrics, medical image analysis is a litmus test as to whether artificial intelligence systems will actually improve patient outcomes and survival. Secondly, it provides a testbed for human-AI interaction, of how receptive patients will be towards healthaltering choices being made, or assisted by a non-human actor.

A. TYPES OF MEDICAL IMAGING

There is a myriad of imaging modalities, and the frequency of their use is increasing. Smith-Bindman *et al.* [2] looked at imaging use from 1996 to 2010 across six large integrated healthcare systems in the United States, involving 30.9 million imaging examinations. The authors found that over the study period, CT, MRI and PET usage increased 7.8%, 10% and 57% respectively. Modalities of digital medical images include ultrasound (US), X-ray, computed tomography (CT) scans and magnetic- resonance imaging (MRI) scans, positron emission tomography (PET) scans, retinal photography, histology slides, and dermoscopy images. Fig. 1. shows some example medical images. Some of these modalities examine multiple organs (such as CT, MRI) while others are organ specific (retinal photography, dermoscopy). The amount of data generated from each study also varies. A histology slide is an image file of a few megabytes while a single MRI may be a few hundred megabytes. This has technical implications on the way the data is pre-processed, and on the design of an algorithm's architecture, in the context of processor and memory limitations

II. LITERATURE REVIEW

The symbolic AI paradigm of the 1970s led to the development of rule-based, expert systems. One early implementation in medicine was the MYCIN system by Shortliffe [3], which suggested different regimes of antibiotic therapies for patients. Parallel to these developments, AI algorithms moved from heuristics-based techniques to manual, handcrafted feature extraction techniques. and then to supervised learning techniques. Unsupervised machine learning methods are also being researched, but the majority of the algorithms from 2015-2017 in the published literature have employed supervised learning methods, namely Convolutional Neural Networks (CNN) [4]. Aside from the availability of large labelled data sets being available, hardware advancements in Graphical Processing Units (GPUs) have also led to improvements in CNN performance, and their widespread use in medical image analysis.McCulloch and Pitts [5] described the first artificial neuron in 1943, which developed into the perceptron posited by Rosenblatt [6] in 1958. In essence, an artificial neural network is a layer of connected perceptrons linking inputs and outputs, and deep neural networks are multiple layers of artficial neural networks. The advantage of a deep neural network is its ability to automatically learn significant low level features (such as lines or edges), and amalgamate them to higher level features (such as shapes) in the subsequent layers. Interestingly, this is how the mammalian and human visual cortices are thought to process visual information and recognize objects [7]. CNNs may have their origins in the Neocognitron concept proposed by Fukushima [8] in 1982, but it was Lecun *et al.* [9] who formalized CNNs and used the error backpropagation described by Rumelhart *et al.* [10], to successfully perform the automatic recognition of handwritten digits. The widespread use of CNNs in image recognition came about after Krizhevsky *et al.* [11] won the 2012 Imagenet Large Scale Visual Recognition Challenge (ILSVRC) with a CNN that had a 15% error rate. The runner up had almost double the error rate at 26%. Krizhevsky *et al.* introduced signiflcant concepts that are used in CNNs today, including the use of Rectified Linear Unit (RELU) functions in CNNs, data augmentation and dropout. Since then, CNNs have featured as the most used architecture in every ILSVRC competition, surpassing human performance at recognizing images in 2015. Correspondingly, there has been a dramatic increase in the number of research papers published on CNN architecture and applications, such that CNNs have become the dominant architecture in medical image analysis. Both the 2-dimensional and 3-dimensional structures of an organ being studied are crucial in order to identify what is normal versus abnormal. By maintaining these local spatial relationships, CNNs are well-suited to perform image recognition tasks. CNNs have been put to work in many ways, including image classification, localization, detection, segmentation and registration. CNNs are the most popular machine learning algorithm in image recognition and visual learning tasks, due to its unique characteristic of preserving local image relations, while performing dimensionality reduction. This captures important feature relationships in an image (such as how pixels on an edge join to form a line),

and reduces the number of parameters the algorithm has to compute, increasing computational efficiency. CNNs are able to take as inputs and process both 2-dimensional images, as well as 3-dimensional images with minor modifications. This is a useful advantage in designing a system for hospital use, as some modalities like X-rays are 2-dimensional while others like CT or MRI scans are 3-dimensional volumes. CNNs and Recurrent Neural Networks (RNNs) are examples of supervised machine learning algorithms, which require significant amounts of training data. Unsupervised learning algorithms have also been studied for use in medical image analysis. These include Autoencoders, Restricted Boltzmann Machines (RBMs), Deep Belief Networks (DBNs), and Generative Adversarial Networks (GANs). Four reviews are highly recommended; Litjens *et al.* [4] provides a thorough list of papers published in the fleld, Shen *et al.* [12] and Suzuki [13] summarize many of the advances, while Greenspan *et al.* [14] gives a succinct overview of recent important papers. These review articles and a list of relevant books can be found in Table 1. This was collated by searching for books in the Elsevier, IEEE Xplore and Springer databases. We generated a list of the 200 most highly-cited papers from Google Scholar, using the query terms 'deep learning' and 'medical image analysis' in October 2017 using citation software [15]. These were manually vetted to ensure that the returned results were relevant and significant in the field. We limited the papers to those published or prepublished in the last 3 years, although older significant papers are mentioned in this article. Table 2 shows the top 20 papers from this list, and the full list of 200 papers can be found in the Supplementary Data as Table S1. Where available, the datasets used by the authors of various papers in this article are described. The website Grand Challenges in Biomedical Image Analysis (https://grand-challenge.org/allflchallenges) aggregates and links to numerous competitions and their respective image datasets. The Cancer Imaging Archive [16] contains numerous datasets across many organ systems, and the National Institute of Health recently released a tranche of over 100,000 anonymized chest x-rays for research use [17] called ``ChestX-ray 8''. Of note, Nifty-Net (www.niftynet.io) [18] is a useful open source framework that contains many machine learning algorithms, released under an Apache License. It allows researchers to explore CNNs and published machine algorithms, such as V- net, U-net, DeepMedic [19]fl[21], and to share pretrained models. The aim of this report is to provide an overview on the state of machine learning algorithms as applied to medical imaging, with an emphasis on which aspects are most useful to the clinician, as some of the authors are practicing surgeons and radiologists. It is hoped that this perspective aids researchers in moving from being trapped in the local minima of speculative research, to designing implementable systems that will impact medical science and patient care

LITERATURE REVIEW

IN "C.-J. HSIAO, E. HING, AND J. ASHMAN, ``TRENDS IN ELECTRONIC HEALTH RECORD SYSTEM USE AMONG OFFICE-BASED PHYSICIANS: UNITED STATES, 2007fl2012,''*NAT. HEALTH STAT. REP.*, VOL. 75, PP. 1fl18, MAY 2014.": This report presents trends in the adoption of electronic health records (EHRs) by office-based physicians during 2007-2012. Rates of adoption are compared by selected physician and practice characteristics.The National Ambulatory Medical Care Survey (NAMCS) is based on a national probability sample of nonfederal office-based physicians who see patients in an office setting. Prior to 2008, data on physician characteristics were collected through in-person interviews with physicians. To increase the sample for analyzing physician adoption of EHR systems, starting in 2008, NAMCS physician interview data were supplemented with data from an EHR mail survey. This report presents estimates from the 2007 in-person interviews, combined 2008-2010 data from both the in-person interviews and the EHR mail surveys, and 2011-2012 data from the EHR mail surveys. Sample data were weighted to produce national estimates of office-based physician characteristics and their practices

IN "R. SMITH-BINDMAN *ET AL.*, ``USE OF DIAGNOSTIC IMAGING STUDIES AND ASSOCIATED RADIATION EXPOSURE FOR PATIENTS ENROLLED IN LARGE INTEGRATED HEALTH CARE SYSTEMS, 1996fl2010,'' *JAMA*, VOL. 307, NO. 22, PP. 2400fl2409, 2012."

THE USE OF DIAGNOSTIC IMAGING in the Medicare population has increased significantly over the last 2 decades, particularly using expensive new technologies such as computed tomography (CT), magnetic resonance imaging (MRI), and nuclear medicine positron emission tomography (PET).1,2 The development and improvement in these advanced diagnostic imaging technologies is widely credited with leading to earlier and more accurate diagnoses of disease using noninvasive techniques. However, utilization and costs of advanced diagnostic imaging in the United States are high and rapidly growing,3,4 and payments to physicians for diagnostic imaging have had the highest rate of growth among all physician services over the last decade.3,4 Computed tomography and nuclear medicine examinations deliver much higher doses of ionizing radiation than conventional radiographs, and extensive epidemiological evidence has linked exposure to radiation levels in this range with the development of radiationinduced cancers.5,6 It is estimated that 2% of future cancers will result from current imaging use, if imaging continues at current rates.7,8 Most studies that have evaluated patterns of diagnostic imaging have assessed insurance claims for feefor-service insured populations1,9-11 where financial incentives encourage imaging.12,13 No large, multisite studies have assessed imaging trends in integrated health care delivery systems that are clinically and fiscally accountable for the outcomes and health status of the population served.13,14 Understanding imaging utilization and associated radiation exposure in these settings could help us determine how much of the increase in imaging may be independent of direct financial incentives. We conducted a population-based study of diagnostic imaging trends between 1996 and 2010 among members of 6 geographically diverse integrated health care delivery systems that have both care delivery and insurance relationships with their memberpatients. The availability of administrative and electronic medical record data on all health care received— including diagnostic imaging— allowed us to assess patterns of imaging over time as they varied by health system and patient demographics. METHODS The study population includes members enrolled in 1 of 6 health care systems, each of which participates in the HMO Research Network,15 including Group Health Cooperative in Washington State; Kaiser Permanente in Colorado, Georgia, Hawaii, Oregon, and Washington; and Marshfield Clinic and Security Health Plan in Wisconsin. We included all members enrolled in groupand staff-model plans, and in addition to commercial plans, the health system members included enrollees with prepaid Medicaid contracts, statesubsidized prepaid plans, and Medicare Advantage plans.We excluded data for health plan members who purchased fee-for-service (network) plans and patients treated at health plan facilities without being enrolled in the health maintenance organization (HMO) plans because of the high likelihood of incomplete capture of imaging data for these patients. Enrollees were included in the study for each year in which they were continuously enrolled. A data resource utility called the Virtual Data Warehouse that includes comprehensive diagnostic imaging data was used to capture standardized data from the electronic medical and administrative records.16 A waiver of informed consent was received for each participating health care system. The study was approved by the institutional review board of every health plan included as well as the University of California, San Francisco. Imaging Utilization All diagnostic imaging tests were included regardless of where they were ordered, performed, or interpreted. Imaging procedures done in conjunction with radiation treatment for cancer were not included. Individual health systems contributed data for at least 11 years and up to 15 years, depending on participation in their local Virtual Data Warehouse. Imaging procedures were coded using standardized codes from the International Classification of Diseases, Ninth Revision, Clinical Modification; Current Procedural Terminology, Fourth Edition; and Healthcare Common Procedure Coding System.17 There were 1467 unique imaging codes across all years, and each was mapped to an anatomic area (ie, abdomen/pelvis [abdomen], brain [central nervous system, abbreviated as CNS], breast, cardiovascular, chest, extremity, obstetric, spine, and other/ unknown). Imaging codes for extremity and spine that could not be differentiated were combined as musculoskeletal. Examinations were also characterized by modality (ie, angiography/fluoroscopy, CT, MRI, nuclear medicine [PET, a subset of nuclear medicine categorized separately because of its high cost], radiography, ultrasound, and other/unknown17). Multiple examinations with the same procedure code performed on the same patient on the same day were counted only once to reduce the likelihood of overcounting. Of the 1467 imaging codes, 1068 were associated with the delivery of ionizing radiation, including angiography/ fluoroscopy, CT, nuclear medicine, and radiography. Ultrasound and MRI do not use ionizing radiation and thus were not included. Because CT and nuclear medicine examinations contribute such a large proportion of the radiation exposure from imaging, we newly abstracted additional patient-level data to allow accurate estimation of dose. For CT, we randomly selected patients based on age and sex in each year from across the participating sites who underwent the most frequent CT examination types (n=4188 examinations) and abstracted the primary determinants of dose from each examination (ie, body region imaged, scan length, kilovolt peak [kVp], milliampere [mA] or mA seconds [mAs], rotation time, pitch, and CT manufacturer and model). These technical parameters were abstracted using automated computer programs that extracted these data from the Digital Imaging and Communications in Medicine (DICOM) tags stored in the Picture Archiving and Communications System (PACS). For examinations prior to when each health plan adopted PACS, these parameters were manually abstracted from the stored or printed CT images. Using these parameters, we estimated the effective dose for each CT examination. Effective dose is a metric that takes into account both the amount of radiation to which a person is exposed and the biological effect of that radiation on the exposed organs. It is defined as a dose equivalent to the dose (and subsequent harm) that would have been received had the full body been irradiated by a single source. Thus, a large dose to a single organ might have a similar effective dose, and thus estimated to have a similar future cancer risk, as a smaller dose to the entire body. In general, effective dose is estimated as a weighted average of organ doses, with weights corresponding to the sensitivity of each organ to developing cancer after radiation exposure. We used a new method for estimating organspecific dose based on improved sexand age-specific phantom anatomy using mathematical hybrid phantoms.18,19 Organ-equivalent doses were weighted to generate effective dose by the tissue weighting factors provided in the International Commission on Radiological Protection publication 103.20 For nuclear medicine examinations, effective dose varies by the administered radiopharmaceutical and activity. At a single facility, we collected data on the type and injected volume of radiopharmaceutical for a consecutive sample of 5502 nuclear medicine examinations. Using these data and standard calculations for estimating effective dose for each examination with methods described by the Medical Internal Radiation Dose committee,21 we estimated the dose for each examination type. For mammography, we obtained unpublished patient-level data from the American College of Radiology Imaging Network Digital Mammography Imaging Screening Trial to estimate dose and variation in dose.22 For the remaining imaging study types (ie, less common CT types, fluoroscopy, angiography/fluoroscopy, and radiography), we completed a detailed review of the published literature to estimate dose and measure of variability in dose for each study. The dosage data provided detailed information on the variability in effective radiation dose within procedure type. We used this information to create a dose estimate that accounts for the variability of dose. A truncated lognormal distribution was a good fit to dose data, with the truncation occurring at 3 SDs on the log scale. For each examination each patient underwent during the study period, we randomly imputed a dose value from the lognormal distribution. This technique allowed each person to be assigned a dose value that reflected the true underlying distribution in dose, rather than assuming each person received the mean dose associated with a particular examination type. We used the data describing the number of imaging tests and associated radiation dose per test to calculate the total dose of radiation each member received each year of the study and to calculate the collective effective dose to the entire population. To estimate cumulative annual radiation exposure for each patient, we summed the doses for each examination within each year. If patients underwent more than 1 examination using the same modality on the same anatomic area on the same day, we only included the examination with the highest radiation exposure to calculate dose so as not to overestimate doses received. Statistical Analysis We calculated the number of imaging examinations per 1000 enrollees per year (rates) by modality, anatomic area, and health system (overall and stratified by site and age). The calculations of rates over time were adjusted for site, age, and sex. This standardization was performed in Stata (StataCorp) by fitting log-linear regression models with Gaussian errors, including site, age, sex, and year as covariates. Based on the fitted model, we estimated average rates using marginal standardization, treating each site with equal weight and adjusting to the observed age and sex distribution.23 For modality-specific analyses, we calculated the per capita dose in mSv per person per year by dividing the collective effective dose by the number of individuals (whether exposed to radiation from diagnostic imaging or not). For analyses that ignored modality, we estimated the individual radiation dose per year and calculated descriptive statistics in annual radiation exposure, including the percentage of enrollees who underwent a high annual radiation exposure (defined as 20-50 mSv)11,20 or a very high radiation exposure (50 mSv).11,20 We calculated the relative contribution (mean dose and percentage of dose) from the different imaging modalities over time. When showing imaging rates (TABLE 1), we show data from 2008, the most recent year where all sites contributed data. We used SAS version 9.2 (SAS Institute) and Stata versions 11.1 and 12.0 for statistical analysis. All statistical tests were 2-sided and significance was set at P.05.

IN "G. LITJENS *ET AL.* (JUN. 2017). ``A SURVEY ON DEEP LEARNING IN MEDICAL IMAGE ANALYSIS." Deep learning algorithms, in particular convolutional networks, have rapidly become a methodology of choice for analyzing medical images. This paper reviews the major deep learning concepts pertinent to medical image analysis and summarizes over 300 contributions to the field, most of which appeared in the last year. We survey the use of deep learning for image classification, object detection, segmentation, registration, and other tasks. Concise overviews are provided of studies per application area: neuro, retinal, pulmonary, digital pathology, breast, cardiac, abdominal, musculoskeletal. We end with a summary of the current state-of-the-art, a critical discussion of open challenges and directions for future research As soon as it was possible to scan and load medical images into a computer, researchers have built systems for automated analysis. Initially, from the 1970s to the 1990s, medical image analysis was done with sequential application of low-level pixel processing (edge and line detector filters, region growing) and mathematical modeling (fitting lines, circles and ellipses) to construct compound rule-based systems that solved particular tasks. There is an analogy with expert systems with many if-then-else statements that were popular in artificial intelligence in the same period. These expert systems have been described as GOFAI (good old-fashioned artificial intelligence) (Haugeland, 1985) and were often brittle; similar to rule-based image processing systems. At the end of the 1990s, supervised techniques, where training data is used to develop a system, were becoming increasingly popular in medical image analysis. Examples include active shape models (for segmentation), atlas methods (where the atlases that are fit to new data form the training data), and the concept of feature extraction and use of statistical classifiers (for computeraided detection and diagnosis). This pattern recognition or machine learning approach is still very popular and forms the basis of many successful commercially available medical image analysis systems. Thus, we have seen a shift from systems that are completely designed by humans to systems that are trained by computers using example data from which feature vectors are extracted. Computer algorithms determine the optimal decision boundary in the high-dimensional feature space. A crucial step in the design of such systems is the extraction of discriminant features from the images. This process is still done by human researchers and, as such, one speaks of systems with handcrafted features. A logical next step is to let computers learn the features that optimally represent the data for the problem at hand. This concept lies at the basis of many deep learning algorithms: models (networks) composed of many layers that transform input data (e.g. images) to outputs (e.g. disease present/absent) while learning increasingly higher level features. The most successful type of models for image analysis to date are convolutional neural networks (CNNs). CNNs contain many layers that transform their input with convolution filters of a small extent. Work on CNNs has been done since the late seventies (Fukushima, 1980) and they were already applied to medical image analysis in 1995 by Lo et al. (1995). They saw their first successful real-world application in LeNet (LeCun et al., 1998) for hand-written digit recognition. Despite these initial successes, the use of CNNs did not gather momentum until various new techniques were developed for efficiently training deep networks, and advances were made in core computing systems. The watershed was the contribution of Krizhevsky et al. (2012) to the ImageNet challenge in December 2012. The proposed CNN, called AlexNet, won that competition by a large margin. In subsequent years, further progress has been made using related but deeper architectures (Russakovsky et al., 2014). In computer vision, deep convolutional networks have now become the technique of choice. The medical image analysis community has taken notice of these pivotal developments. However, the transition from systems that use handcrafted features to systems that learn features from the data has been gradual. Before the breakthrough of AlexNet, many different techniques to learn features were popular. Bengio et al. (2013) provide a thorough review of these techniques. They include principal component analysis, clustering of image patches, dictionary approaches, and many more. Bengio et al. (2013) introduce CNNs that are trained end-to-end only at the end of their review in a section entitled Global training of deep models. In this survey, we focus particularly on such deep models, and do not include the more traditional feature learning approaches that have been applied to medical images. For a broader review on the application of deep learning in health informatics we refer to Ravi et al. (2017), where medical image analysis is briefly touched upon. Applications of deep learning to medical image analysis first started to appear at workshops and conferences, and then in journals. The number of papers grew rapidly in 2015 and 2016. This is illustrated in Fig. 1. The topic is now dominant at major conferences and a first special issue appeared of IEEE Transaction on Medical Imaging in May 2016 (Greenspan et al., 2016). One dedicated review on application of deep learning to medical image analysis was published by Shen et al. (2017). Although they cover a substantial amount of work, we feel that important areas of the field were not represented. To give an example, no work on retinal image analysis was covered. The motivation for our review was to offer a comprehensive overview of (almost) all fields in medical imaging, both from an application and a methodology driven perspective. This also includes overview tables of all publications which readers can use to quickly assess the field. Last, we leveraged our own experience with the application of deep learning methods to medical image analysis to provide readers with a dedicated discussion section covering the state-of-the-art, open challenges and overview of research directions and technologies that will become important in the future. This survey includes over 300 papers, most of them recent, on a wide variety of applications of deep learning in medical image analysis. To identify relevant contributions PubMed was queried for papers containing (“convolutional” OR “deep learning”) in title or abstract. ArXiv was searched for papers mentioning one of a set of terms related to medical imaging. Additionally, conference proceedings for MICCAI (including workshops), SPIE, ISBI and EMBC were searched based on titles of papers. We checked references in all selected papers and consulted colleagues. We excluded papers that did not report results on medical image data or only used standard feed-forward neural networks with handcrafted features. When overlapping work had been reported in multiple publications, only the publication(s) deemed most important were included. We expect the search terms used to cover most, if not all, of the work incorporating deep learning methods. The last update to the included papers was on February 1, 2017. The appendix describes the search process in more detail. Summarizing, with this survey we aim to: • show that deep learning techniques have permeated the entire field of medical image analysis; • identify the challenges for successful application of deep learning to medical imaging tasks; • highlight specific contributions which solve or circumvent these challenges. The rest of this survey is structured as followed. In Section 2, we introduce the main deep learning techniques that have been used for medical image analysis and that are referred to throughout the survey. Section 3 describes the contributions of deep learning to canonical tasks in medical image analysis: classification, detection, segmentation, registration, retrieval, image generation and enhancement. Section 4 discusses obtained results and open challenges in different application areas: neuro, ophthalmic, pulmonary, digital pathology and cell imaging, breast, cardiac, abdominal, musculoskeletal, and remaining miscellaneous applications. We end with a summary, a critical discussion and an outlook for future research.

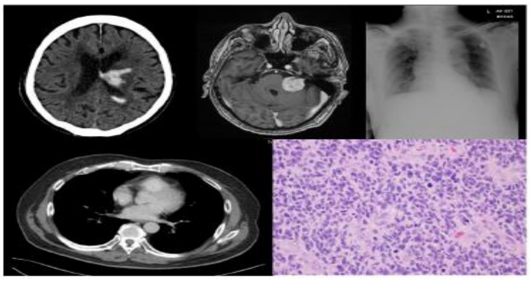
IN “A SURVEY ON DEEP LEARNING IN MEDICAL IMAGE ANALYSIS”

deep learning algorithms, in particular convolutional networks, have rapidly become a methodology of choice for analyzing medical images. this paper reviews the major deep learning concepts pertinent to medical image analysis and summarizes over 300 contributions to the field, most of which appeared in the last year. we survey the use of deep learning for image classification, object detection, segmentation, registration, and other tasks and provide concise overviews of studies per application area. open challenges and directions for future research are discussed

III. SYSTEM ANALYSIS AND DESIGN

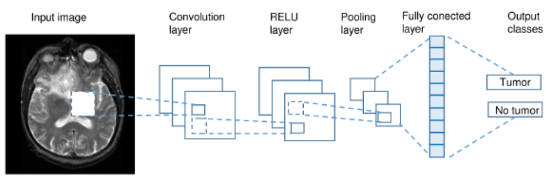
EXISTING SYSTEM:

There is a myriad of imaging modalities, and the frequency of their use is increasing. Smith-Bindman *et al.* [2] looked at imaging use from 1996 to 2010 across six large integrated healthcare systems in the United States, involving 30.9 million imaging examinations. The authors found that over the study period, CT, MRI and PET usage increased 7.8%, 10% and 57% respectively.



The symbolic AI paradigm of the 1970s led to the development of rule-based, expert systems. One early implementation in medicine was the MYCIN system by Shortliffe [3], which suggested different regimes of antibiotic therapies for patients. Parallel to these developments, AI algorithms moved from heuristics-based techniques to manual, handcrafted feature extraction techniques. and then to supervised learning techniques. Unsupervised machine learning methods are also being researched, but the majority of the algorithms from 2015-2017 in the published literature have employed supervised learning methods,

PROPOSED SYSTEM:

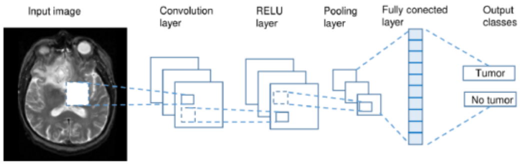


Currently, CNNs are the most researched machine learning algorithms in medical image analysis [4]. The reason for this is that CNNs preserve spatial relationships when filtering input images. As mentioned, spatial relationships are of crucial importance in radiology, for example, in how the edge of a bone joins with muscle, or where normal lung tissue interfaces with cancerous tissue. As shown in Fig. 2., a CNN takes an input image of raw pixels, and transforms it via Convolutional Layers, Rectified Linear Unit (RELU) Layers and Pooling Layers. This feeds into a final Fully Connected Layer which assigns class scores or probabilities, thus classifying the input into the class with the highest probability.

Detection, sometimes known as Computer-Aided Detection (CADe) is a keen area of study as missing a lesion on a scan can have drastic consequences for both the patient and the clinician. The task for the Kaggle Data Science Bowl of 2017 [64] involved the detection of cancerous lung nodules on CT lung scans. Approximately 2000 CT scans were released for the competition and the winner Fangzhou [65] achieved a logarithmic loss score of 0.399. Their solution used a 3-D CNN inspired by U-Net architecture [19] to isolate local patches first for nodule detection. Then this output was fed into a second stage consisting of 2 fully connected layers for classification of cancer probability. Shin *et al.* [24] evaluated five well-known CNN architectures in detecting thoracoabdominal lymph nodes and Interstitial lung disease on CT scans. Detecting lymph nodes is important as they can be a marker of infection or cancer. They achieved a mediastinal lymph node detection AUC score of 0.95 with a sensitivity of 85% using GoogLeNet, which was state of the art. They also documented the benefits of transfer learning, and the use of deep learning architectures of up to 22 layers, as opposed to fewer layers which was the norm in medical image analysis. Overfeat was a CNN pre-trained on natural images that won the ILSVRC 2013 localization task [66]. Ciompi *et al.* [67] applied Overfeat to 2-dimensional slices of CT lung scans oriented in the coronal, axial and sagittal planes, to predict the presence of nodules within and around lung fissures. They combined this approach with simple SVM and RF binary classifiers, as well as a Bag of

Frequencies [68], a novel 3-dimensional descriptor of their own invention.

SYSTEM ARCHITECTURE



IV. SYSTEM IMPLEMENTATION

The symbolic AI paradigm of the 1970s led to the development of rule-based, expert systems. One early implementation in medicine was the MYCIN system by Shortliffe [3], which suggested different regimes of antibiotic therapies for patients. Parallel to these developments, AI algorithms moved from heuristics-based techniques to manual, handcrafted feature extraction techniques. and then to supervised learning techniques. Unsupervised machine learning methods are also being researched, but the majority of the algorithms from 2015-2017 in the published literature have employed supervised learning methods, namely Convolutional Neural Networks (CNN) [4]. Aside from the availability of large labelled data sets being available, hardware advancements in Graphical Processing Units (GPUs) have also led to improvements in CNN performance, and their widespread use in medical image analysis. McCulloch and Pitts [5] described the flrst artiflcial neuron in 1943, which developed into the perceptron posited by Rosenblatt [6] in 1958. In essence, an artiflcial neural network is a layer of connected perceptrons linking inputs and outputs, and deep neural networks are multiple layers of artiflcial neural networks. The advantage of a deep neural network is its ability to automatically learn signiflcant low level features (such as lines or edges), and amalgamate them to higher level features (such as shapes) in the subsequent layers. Interestingly, this is how the mammalian and human visual cortices are thought to process visual information and recognize objects [7]. CNNs may have their origins in the Neocognitron concept proposed by Fukushima [8] in 1982, but it was Lecun *et al.* [9] who formalized CNNs and used the error backpropagation described by Rumelhart *et al.* [10], to successfully perform the automatic recognition of handwritten digits. The widespread use of CNNs in image recognition came about after Krizhevsky *et al.* [11] won the 2012 Imagenet Large Scale Visual Recognition Challenge (ILSVRC) with a CNN that had a 15% error rate. The runner up had almost double the error rate at 26%. Krizhevsky *et al.* introduced signiflcant concepts that are -used in CNNs today, including the use of Rectifled Linear Unit (RELU) functions in CNNs, data augmentation and dropout. Since then, CNNs have featured as the most used architecture in every ILSVRC competition, surpassing human performance at recognizing images in 2015. Correspondingly, there has been a dramatic increase in the number of research papers published on CNN architecture and applications, such that CNNs have become the dominant architecture
in medical image analysis.

CONVOLUTIONAL NEURAL NETWORKS

Both the 2-dimensional and 3-dimensional structures of an organ being studied are crucial in order to identify what is normal versus abnormal. By maintaining these local spatial relationships, CNNs are well-suited to perform image\ recognition tasks. CNNs have been put to work in many ways, including image classiflcation, localization, detection, segmentation and registration. CNNs are the most popular machine learning algorithm in image recognition and visual learning tasks, due to its unique characteristic of preserving local image relations, while performing dimensionality reduction. This captures important feature relationships in an image (such as how pixels on an edge join to form a line), and reduces the number of parameters the algorithm has to compute, increasing computational efflciency. CNNs are able to take as inputs and process both 2-dimensional images, as well as 3-dimensional images with minor modiflcations. This is a useful advantage in designing a system for hospital use, as some modalities like X-rays are 2-dimensional while others like CT or MRI scans are 3-dimensional volumes. CNNs and Recurrent Neural Networks (RNNs) are examples of supervised machine learning algorithms, which require signiflcant amounts of training data. Unsupervised learning algorithms have also been studied for use in medical image analysis. These include Autoencoders, Restricted Boltzmann Machines (RBMs), Deep Belief Networks (DBNs), and Generative Adversarial Networks (GANs).

D. RESOURCES

Four reviews are highly recommended; Litjens *et al.* [4] provides a thorough list of papers published in the fleld, Shen *et al.* [12] and Suzuki [13] summarize many of the advances, while Greenspan *et al.* [14] gives a succinct overview of recent important papers. These review articles and a list of relevant books can be found in Table 1. This was collated by searching for books in the Elsevier, IEEE Xplore and Springer databases. We generated a list of the 200 most highly-cited papers from Google Scholar, using the query terms 'deep learning' and 'medical image analysis' in\ October 2017 using citation software [15]. These were manually vetted to ensure that the returned results were relevant\ and signiflcant in the fleld. We limited the papers to those published or prepublished in the last 3 years, although older signiflcant papers are mentioned in this article. Table 2 shows the top 20 papers from this list, and the full list of 200 papers can be found in the Supplementary Data as Table S1. Where available, the datasets used by the authors of various papers in this article are described. The website Grand Challenges in Biomedical Image Analysis (https://grand-challenge.org/allflchallenges) aggregates and links to numerous competitions and their respective image datasets. The Cancer Imaging Archive [16] contains numerous datasets across many organ systems, and the National Institute of Health recently released a tranche of over 100,000 anonymized chest x-rays for research use [17] called ``ChestX-ray 8''. Of note, Nifty-Net (www.niftynet.io) [18] is a useful open source framework that contains many machine learning algorithms, released under an Apache License. It allows researchers to explore CNNs and published machine algorithms, such as V- net, U-net, DeepMedic [19]fl[21], and to share pretrained models. The aim of this report is to provide an overview on the state of machine learning algorithms as applied to medical imaging, with an emphasis on which aspects are most useful to the clinician, as some of the authors are practicing surgeons and radiologists. It is hoped that this perspective aids researchers in moving from being trapped in the local minima of speculative research, to designing implementable systems that will impact medical science and patient care

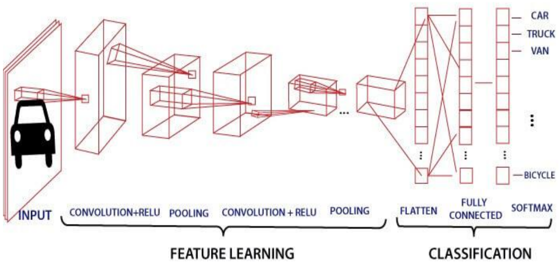
ALGORITHM

CONVOLUTIONAL NEURAL NETWORK

Convolutional Neural Network is one of the main categories to do image classification and image recognition in neural networks. Scene labeling, objects detections, and face recognition, etc., are some of the areas where convolutional neural networks are widely used.

CNN takes an image as input, which is classified and process under a certain category such as dog, cat, lion, tiger, etc. The computer sees an image as an array of pixels and depends on the resolution of the image. Based on image resolution, it will see as **h * w * d**, where h= height w= width and d= dimension. For example, An RGB image is **6 * 6 * 3** array of the matrix, and the grayscale image is **4 * 4 * 1** array of the matrix.

In CNN, each input image will pass through a sequence of convolution layers along with pooling, fully connected layers, filters (Also known as kernels). After that, we will apply the Soft-max function to classify an object with probabilistic values 0 and 1.



Convolution Layer

Convolution layer is the first layer to extract features from an input image. By learning image features using a small square of input data, the convolutional layer preserves the relationship between pixels. It is a mathematical operation which takes two inputs such as image matrix and a kernel or filter.

- The dimension of the image matrix is **h×w×d**.
- The dimension of the filter is **f_h×f_w×d**.
- The dimension of the output is **($h-f_h+1$)×($w-f_w+1$)×1**.

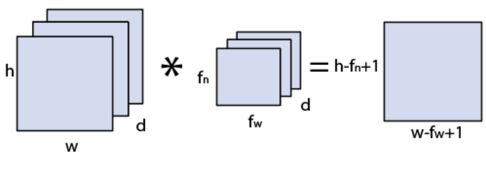


Image matrix multiplies kernl or filter matrix

Let's start with consideration a 5*5 image whose pixel values are 0, 1, and filter matrix 3*3 as:

$$\begin{bmatrix}1&1&1&0&0\\0&1&1&1&0\\0&0&1&1&1\\0&0&1&1&0\\0&1&1&0&0\end{bmatrix} \times \begin{bmatrix}1&0&1\\0&1&0\\1&0&1\end{bmatrix}$$

5 × 5 – Image Matrix 3 × 3 – Filter Matrix

The convolution of 5*5 image matrix multiplies with 3*3 filter matrix is called "**Features Map**" and show as an output.

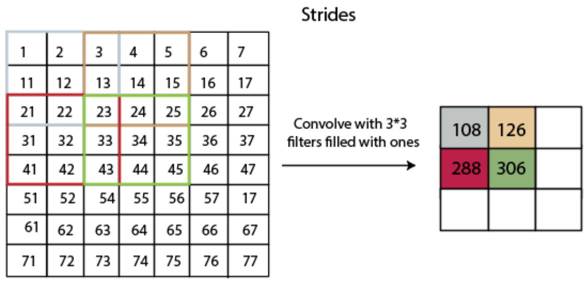
$$\begin{bmatrix}1&1&1&0&0\\0&1&1&1&0\\0&0&1&1&1\\0&0&1&1&0\\0&1&1&0&0\end{bmatrix} \times \begin{bmatrix}1&0&1\\0&1&0\\1&0&1\end{bmatrix} = \begin{bmatrix}4&3&4\\2&4&3\\2&3&4\end{bmatrix}$$

Convolved Feature

Convolution of an image with different filters can perform an operation such as blur, sharpen, and edge detection by applying filters.

Strides

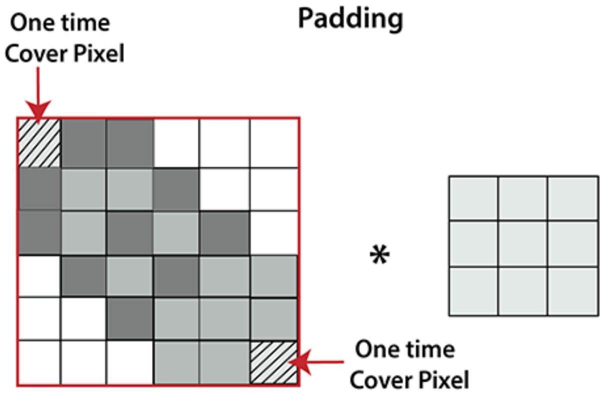
Stride is the number of pixels which are shift over the input matrix. When the stride is equaled to 1, then we move the filters to 1 pixel at a time and similarly, if the stride is equaled to 2, then we move the filters to 2 pixels at a time. The following figure shows that the convolution would work with a stride of 2.



Padding

Padding plays a crucial role in building the convolutional neural network. If the image will get shrink and if we will take a neural network with 100's of layers on it, it will give us a small image after filtered in the end.

If we take a three by three filter on top of a grayscale image and do the convolving then what will happen?



It is clear from the above picture that the pixel in the corner will only get covers one time, but the middle pixel will get covered more than once. It means that we have more information on that middle pixel, so there are two downsides:

- Shrinking outputs
- Losing information on the corner of the image.

To overcome this, we have introduced padding to an image. **"Padding is an additional layer which can add to the border of an image."**

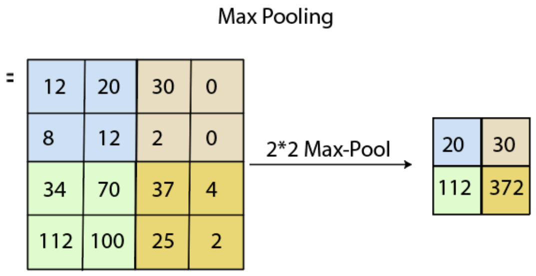
Pooling Layer

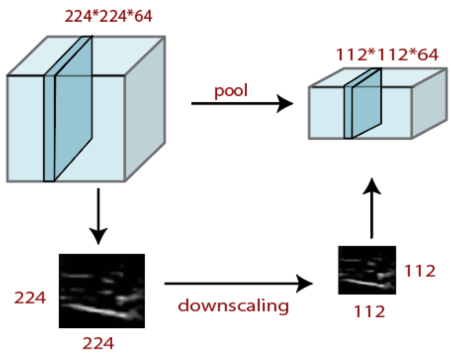
Pooling layer plays an important role in pre-processing of an image. Pooling layer reduces the number of parameters when the images are too large. Pooling is "**downscaling**" of the image obtained from the previous layers. It can be compared to shrinking an image to reduce its pixel density. Spatial pooling is also called downsampling or subsampling, which reduces the dimensionality of each map but retains the important information. There are the following types of spatial pooling:

Max Pooling

Max pooling is a **sample-based discretization process**. Its main objective is to downscale an input representation, reducing its dimensionality and allowing for the assumption to be made about features contained in the sub-region binned.

Max pooling is done by applying a max filter to non-overlapping sub-regions of the initial
representation.





Average Pooling

Down-scaling will perform through average pooling by dividing the input into rectangular pooling regions and computing the average values of each region.

Syntax

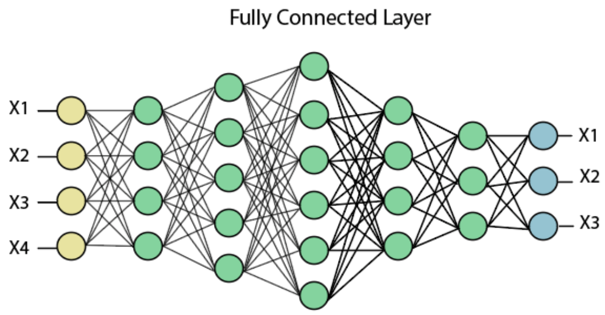
layer = averagePooling2dLayer(poolSize)
layer = averagePooling2dLayer(poolSize,Name,Value)

Sum Pooling

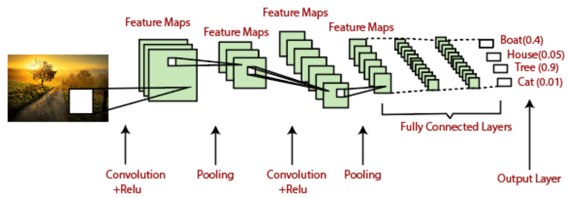
The sub-region for **sum pooling** or **mean pooling** are set exactly the same as for **max-pooling** but instead of using the max function we use sum or mean.

Fully Connected Layer

The fully connected layer is a layer in which the input from the other layers will be flattened into a vector and sent. It will transform the output into the desired number of classes by the network.



In the above diagram, the feature map matrix will be converted into the vector such as **x1, x2, x3... xn** with the help of fully connected layers. We will combine features to create a model and apply the activation function such as **softmax** or **sigmoid** to classify the outputs as a car, dog, truck, etc.



V. CONCLUSION

This study examined the applications of deep learning in medical image analysis for brain tumor detection and classification. The proposed framework utilizes advanced deep learning architectures to analyze medical imaging data, automatically extract relevant features, and accurately identify tumor regions. Experimental observations indicate that deep learning models significantly improve diagnostic accuracy, reduce human intervention, and enhance the efficiency of medical image interpretation. Furthermore, automated tumor segmentation and classification assist healthcare professionals in early diagnosis, treatment planning, and disease monitoring. The ability of deep learning systems to learn complex image representations enables reliable detection of various brain tumor types while minimizing diagnostic errors. The proposed approach contributes to improved healthcare outcomes and supports the development of intelligent clinical decision-support systems. Future research may focus on integrating transformer-based architectures, multimodal medical imaging, explainable artificial intelligence, and real-time diagnostic platforms to further enhance brain tumor analysis and precision healthcare applications.

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