Automatic Neuroimage Processing and Analysis in Stroke—A Systematic Review

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***Abstract*—This article presents a systematic review of the current computational technologies applied to medical images for the detection, segmentation, and classification of strokes. Besides, analyzing and evaluating the technological advances, the challenges to be overcome and the future trends are discussed. The principal approaches make use of artificial intelligence, digital image processing and analysis, and various other technologies to develop computer-aided diagnosis (CAD) systems to improve the accuracy in the diagnostic process, as well as the interpretation consistency of medical images. However, there are some points that require greater attention such as low sensitivity, optimization of the algorithm, a reduction of false positives, and improvement in the identification and segmentation processes of different sizes and shapes. Also, there is a need to improve the classification steps of different stroke types and subtypes. Furthermore, there is an additional need for further research to improve the current techniques and develop new algorithms to overcome disadvantages identified here. The main focus of this research is to analyze the applied technologies for the development of CAD systems and verify how effective they are for stroke detection, segmentation, and classification. The main contributions of this review are that it analyzes only up-to-date studies, mainly from 2015 to 2018, as well as organizing the various studies in the area according to the research proposal, i.e., detection, segmentation, and classification of the types of stroke and the respective techniques used. Thus, the review has great relevance for future research, since it presents an ample comparison of the most recent works in the area, clearly showing the existing difficulties and the models that have been proposed to overcome such difficulties.**

***Index Terms*—Artificial intelligence, CAD system, classification, detection, neuroimaging, segmentation, stroke.**

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I. Introduction

A STROKE is a lesion which abruptly attacks the cerebral parenchyma. It is caused by an interruption in the blood flow for a specific region of the brain. This, in turn, interrupts oxygen and nutrients, which results in functional losses in the brain [1], [2]. There are two types of stroke: ischemic and hemorrhagic. An ischemic stroke is due to the obstruction of a blood vessel while a hemorrhagic stroke occurs when there is a rupture of a blood vessel. There is an ischemic stroke subtype known as transient ischemic attack (TIA) that is characterized by a temporary block of the blood vessel. Unlike the ischemic stroke, this subtype lasts less than five hours and does not cause permanent damage to the brain [3]. Among the many causes of stroke, the principal ones are related to problems in the organism which affect the blood flow, such as: atherosclerosis, cardiac arrhythmias, cardiac insufficiency, acute myocardial infarction, heart valve diseases and blood coagulation disorders. However, strokes can also be provoked by other factors, such as: alcohol, smoking, hypertension, obesity and diabetes [4]. Determining the type of stroke depends fundamentally on the mechanism that originated it and the effects depend on which part of the brain was injured and how critically it has been affected [5].

The World Health Organization (WHO) estimates that 6.7 of 17.7 million deaths due to cardiovascular disease in 2012 were caused by a stroke [5]. This puts stroke among the three main causes of the premature mortality [6]. Besides WHO, the American Heart Association (AHA) and the American Stroke Association (ASA) also confirm that strokes are the second most common cause of death worldwide and that strokes were responsible for more than 6 million deaths globally in 2014, 2015 and 2016 [6]–[8]. Another important problem related to a stroke, is that many survivors have chronic consequences that are complex and heterogeneous. According to data from AHA, there are an estimated about 2 million people with sequelae in the United States, and this caused costs of approximately U$ 316.1 billion between 2012 and 2013. This value includes U$ 189.7 billion in expenses with direct costs, such as doctors and other professionals, hospital services, prescribed medication and home health care. But it does not include the nursing care and U$ 126.4 billion of indirect costs with the loss of productivity attributed to stroke. By 2030, these values are expected to have grown to U$ 918 billion [9].

Although mortality rates have declined in recent decades, the high level of these rates is still alarming [10], [11]. Therefore, treatments that can mitigate the consequences are essential and a fast diagnose of a patient is one of the most important steps since each type of stroke requires a specific treatment [3]. The latest AHA and ASA guidelines recommended that patients with suspected or reoccurring stroke should receive coagulation medications including a tissue plasminogen activator (tPA) and other treatments within one hour after the stroke identification to minimize brain damage and accelerate recovery [12]. The initial evaluation of a patient with signs of stroke should be brief and systematic, but a neurologist is needed to confirm the clinical suspicion and, many times, this is a time consuming task. He/She will identify the type of stroke and its location, through imaging, and thus be able to establish the therapy and the inclusion or exclusion criteria to determine other therapeutic measures to be performed as well as obtain the parameters for patient follow-up.

Since the discovery of X-rays, medical imaging has evolved exponentially. Among the various modalities of medical images, brain images or neuroimages have evolved a significantly in recent years, and are able to show brain structures and functions. Fig. 1 shows some of the most significant advances in neuroimages since the 1960s. Among the various modalities of neuroimaging exams, computed tomography (CT) and magnetic resonance imaging (MRI) stand out, as they provide comprehensive information on cerebral and vascular health. Following the development of these new imaging exams, neuroimaging processing has also evolved significantly, assisting specialists to confirm diagnoses quickly, with greater confidence and helping in treatment choices. In cases of stroke, CT is the most suitable technique, since it has a lower cost, is faster and allows the extension and severity of the lesion to be verified, besides it is less affected by noise. Although MRI is more sensitive, its limitation such as the time of the exam and the set-up costs, make it impossible to use on a large scale [13], [14]. Subtle changes in CT images may characterize regions of edema that result in stroke. Early identification of these changes is still a challenge and depends only on the experience of the specialist [15]. In order to overcome this dependence, computer aided diagnosis (CAD) systems have reduced the time of evaluation of the exams and the number of false positives, increasing the accuracy of the diagnosis. A system of medical diagnosis is important and very useful when we consider the need to interpret the neuroimaging data, to identify the type of lesion and the possible temporary unavailability of a radiologist [16], [17].

The reviews found in the Web of Science databases only exposed the data about the incidence of stroke grouped by time, demographically, by gender, race and risk factors or aggravation of the diseases. Some reviews only analyzed the types of exams and images used for the study and diagnosis of strokes by clinical specialists and researchers, such as [22], which discusses existing imaging methods, but does not discuss the automatic methods developed which detect, target and classify strokes. The research in [23] presents non-invasive imaging techniques that provide complementary information on strokes.The review details the exams that are performed *in vivo*, through the analysis of vascular characteristics and may help in the recovery of patients who suffered a stroke. These two reviews are from 2013 and 2014, respectively, i.e., they were published some time ago, in addition, these works do not address the automatic methods of detection, segmentation and classification of strokes, many of which have only been developed more recently. There are few review papers that cover the different methodologies and techniques for the detection, segmentation and classification of strokes in various types of medical images. In the review of [24], the authors discussed the machine learning (ML) techniques to detect and segment brain lesions from MRI. They presented results confirming that these methods are flexible and efficient for the detection of brain tumors, lacunar infarcts and areas with white matter hyperintensities; furthermore they can be linked up to a CAD system. Although the review presents neuroimaging analysis techniques used in CAD systems for stroke and brain tumors, the work focuses only on MRI exams, leaving a margin for CT, ultrasound and nuclear medical examinations. Another recent research developed by [25] investigated deep learning techniques to analyze medical images. The authors concluded that convolutional neural networks (CNN) have become one of the most studied and used methodologies to analyze medical images. The study provides concise summaries in specific areas, such as: neurological pathology, pulmonary, digital pathology, breast, cardiac, abdominal and musculoskeletal. However, the work does not address the problem of stroke and almost all the methods mentioned are focused on the cerebral MRI. No review covering the use of artificial intelligence (AI) with these new techniques and methodologies applied to neuroimages with the objective of detection, segmentation and classification of strokes was found in the literature. Therefore, this review presents different methodologies, techniques and methods which can compose a CAD system and that can help to deal with this pathology, besides presenting a systematic comparison about the automatic techniques for the detection, segmentation and classification of strokes using different types of neuroimaging exams.

This review brings various contributions to students, researchers, medical professionals, hospitals, etc., and the main ones based on the recent literature of the area, are presented in bullet form here:

1) we provide an investigation into recent approaches and computational tools from 2015 to 2018 used to help doctors (specialists or residents), radiologist and researchers in the diagnostic and prognostic of strokes.
2) we present a comparison between the most prominent works related to computational methods for the detection, segmentation and classification of strokes. Moreover, we site an example of what is happening in the neuroimaging research field.
3) we give a detailed analysis of the databases publicly available, describing the equipment characteristics and configurations used for acquisition of image analysis.

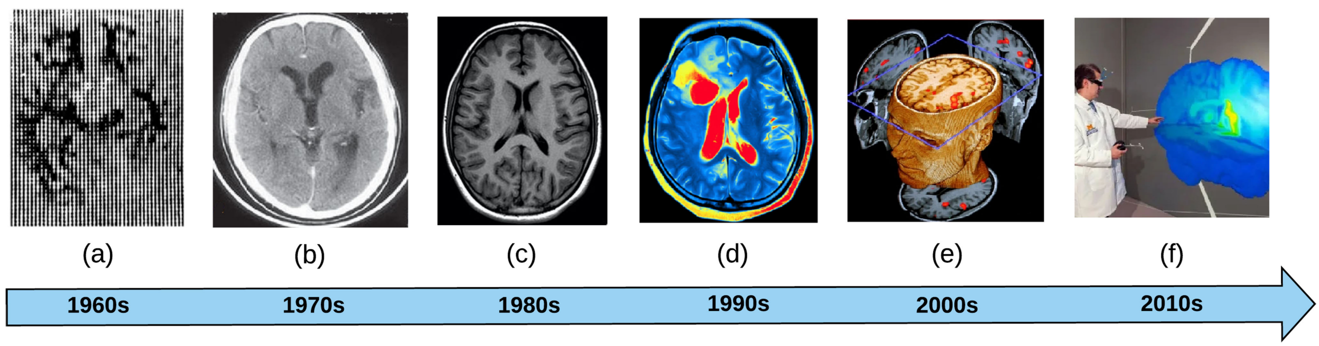


Fig. 1. Evolution in neuroimaging processing over the decades. (a) First neuroimage produced by Hounsfield in EMI Central Research Laboratories, (b)–(d) Images of CT, MRI and PET scan respectively. (e) 3D reconstruction of MRI and (f) a specialist using augmented reality for examine a brain. Adapted from: [18]–[21].

4) we investigate the new technologies which present many advantages in relation to CT and MRI exams, but that still need more detailed research and more efficient tests for validation.
5) we identified and analyzed the challenges that still need to be overcome and, finally, evaluated the future perspectives in this research area.

The paper is organized as follow: Section II presents the methodology used for the selection of each work, describing the scope and limits of the research, Section III presents a summary of each work selected, and describes its objectives, applied methodology, the type of medical image used and the results achieved; in the Section IV we detailed the databases that are publicly available and were used in some related works; Section V shows the main limitations found and the future challenges reported by the researchers; and Section VI treats the errors and possible solutions to improve the mentioned process improvement, as well as the final conclusions of this review.

II. Work Selection Criteria

This article is a systematic review that follows a series of predefined criteria. These criteria include the type of study, the time period of the research, the specific inclusion and exclusion criteria, the databases searched, the evaluation metrics and the relevance of the study results. The purpose of this review is to carry out a critical and comprehensive review of the technical literature, addressing the maximum number of publications within the established time period, as well as the classification in terms of the techniques used, i.e. detection, segmentation and classification of strokes in neuroimaging.

The searches were carried out in the following bibliographic databases: Web of Science, Science Direct, IEEEXplore, PubMed, Plos One, Multidisciplinary Digital Publishing Institute (MDPI), SciVerse Scopus, Springer, SAGE Publishing, Wiley, Frontiers, Nature Research, SAGE Publishing, Scielo, World Scientific Publishing, PubMed Central (PMC) and Hindawi Publishing Corporation. Each bibliographic database has its specificities in the indexing processes; so we opted for the search using controlled vocabulary terms adapted to each search engine. Thus, the research, using this methodology, resulted in a compilation of published works within the pre-established criteria. The search period was from 2015 to 2018. The terms searched were Stroke, Ischemic Stroke, Hemorrhagic Stroke, Detection, Segmentation, Classification, Medical Image, Neuroimaging, Computed Tomography, Magnetic Resonance Imaging and Computer-aided Diagnosis and Internet of Things (IoT). In addition, key words were further combined with logical expressions. All articles which analyzed tumors, edemas and any other research in cerebral diseases that were not strokes, were excluded.

At the first stage of this work all the titles and abstract were read, and from the 1933 initial works, 1400 works were excluded. The remaining 533 selected works went through an analysis of objectives, methodology and results, after that only 214 works remained. These works were fully read in the third stage and 103 works were finally selected. Fig. 2 shows the flowchart used to select the works reviewed based on the selection criteria explained above.

III. CAD Systems For Stroke

Image diagnostics have become an important tool for clinical use. Images exams offer information about the anatomy and physiology of the body interior, or of specific organs. All of this is done in a non invasive way, being safe and painless. However, these images can contain information that is imperceptible to the human vision system, but a computational analysis be used to help obtain this information. The Computer Aided Diagnosis (CAD) system is an efficient tool to obtain a good level of detail to support a clinical diagnosis. The proposal of CAD is not to substitute the doctor, but to assist the specialist in the interpretation of the exams with a system that provides a second opinion or clinical and that is based on automatic quantitative analyses [26].

CAD systems have attracted the attention of scientists, researchers and radiologists as they are a challenging research topic and have a great potential in clinical applications. The development of these systems is of extreme importance for pre-surgical and post-surgical procedures, as it reduces the number of false positives and the time for an accurate diagnostic, as well as a reduction of the inter and intra-variability of

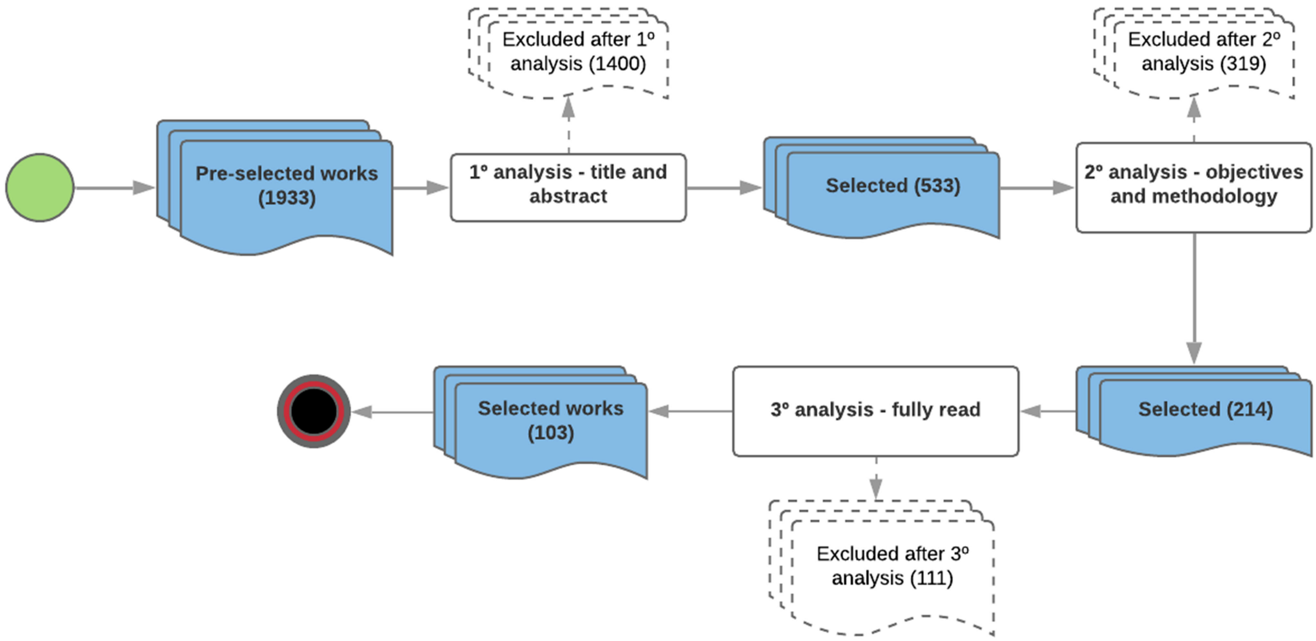


Fig. 2. Flowchart of the selection process of the works searched with the established criteria. The number between brackets is the selected works at each step.

specialists. The technological advances in the last decade and many promising research works have demonstrated the effectiveness of CAD systems [27]. These advances led to the approval of some systems by the Food and Drug Administration (FDA).[1] In 1998, the R2 Technology was the first to get the certification for a CAD system of mammography (ImageChecker). After that the SecondLook system from iCAD Systems from Canada also got the approval for digital mammography in 2001 [28], [29].

The success of CAD in mammography was rapidly replicated for chest radiography. In 2001, the RapidScreen, a CAD system for lung cancer detection in radiography, which was developed by Deus Technologies, was approved. In 2004, the ImageChecker CT, a CAD system for pulmonar CT developed by the R2 Technology, received the certification. Th MeVis LiverAnalyser/LiverViewer Software, which is a software for planning the liver surgery and segmenting lesions, developed by the Medical Diagnostic Systems and Visualizations GmbH (Germany), and was accepted. The Median Technologies from France received approval in 2007 for its LMS-Liver, which is a visualization and analysis software package for the evaluation of hepatic lesions in CT images. The GE Medical Systems software, CT colonography/navigator 2, was approved in 2001 and the Syngo Colonography software package from Siemens Medical Solutions USA was approved in 2003. Both systems allow the user to examine the colon in CT images. Although the FDA has approved many systems for clinical use, there are many requests for certification with approval pending.

CAD systems for stroke have the objective to detect, delineate the region and classifying the type of stroke. Fig. 3 presents the general schematic diagram of CAD systems. The Brain Dock uses these systems for cerebrovascular diseases and they have been widely to detect of asymptomatic brain diseases [30]. Many other systems are still in the first stages of development and have been used only in scientific research [31], [32]. Practical and bureaucratic factors, such as the clinical validation, regulatory and economic approval are limiting factor for the integration of these systems into clinical practice [33].

[1]**Food and Drug Administration (FDA):** Federal Agency of the United States Department of Health and Human Services.

A. Stroke Detection

Among the works that use CT and MRI images, the researchers [15], [34] evaluated the usefulness of the Iterative Model Reconstruction (IMR-Neuro) in the stroke diagnoses in CT images. IMR-Neuro is compared to the filtered back projection (FBP). Both techniques were applied to a database composed of 40 CT exams, 20 control patients and 20 with ischemic stroke, confirmed by diffusion-weighted image (DWI) MRI, known as MRI-DWI, within 24 hours after the CT. The authors compared the performance of 10 radiologists in the detection of hypoattenuation of parenchymal reconstructions of the two techniques using the ROC curves and the jackknife test. Statistical analysis of the results showed that the IMR-Neuro significantly decreased image noise and increased the contrast-to-noise ratio (CNR) of the infarcted area increasing the observer's performance in the detection of the hypoattenuation region. However, the study presents the following limitations: use of a small database that limits the generalization of the results; the infarcted area was confirmed by MRI-DWI exams acquired within 24 hours after CT and therefore there was the possibility of progress or change from the moment of CT; and the difficulty of defining the ROI in the infarcted insula, which depends only on the specialist analysis.

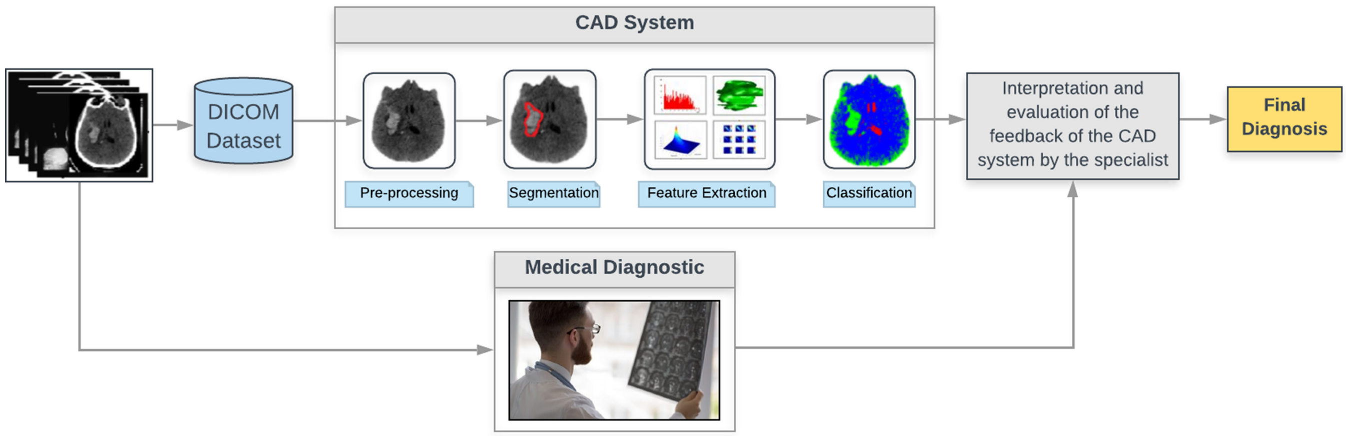


Fig. 3. Common methodology of CAD system for stroke.

Computed tomography without contrast is a high performance diagnostic method as it allows a preliminary analysis that provides a quick way to exclude conditions that may seem to be a stroke. However, the density of a region of the cerebral parenchyma affected by a stroke is very similar to the unaffected regions. This makes the differentiation of an early infarction extremely difficult for a human. Because of this, [35] described the contrast characterization of the ischemic stroke in relation to the normal brain parenchyma in non-contrasted CT images. The authors used a database of 519 exams of 429 anonymous patients with clinically confirmed stroke. The exams were performed as part of a standard stroke diagnosis procedure in the emergency room and during hospital treatment. These exams were acquired by four different CT instruments at two hospital centers in Krakow and Rzeszow, Poland. The infarcts were characterized more efficiently by the mean values of 8.28 HU (Hounsfield Units), 6.60 HU and 7.55 HU, calculated as a difference of 5 consecutive voxels belonging to the lesion and to the parenchyma between all exams. The results evidenced the difficulty of manual or automatic segmentations of strokes in non-contrasted tests, based only on HU or histogram techniques, regardless of the time of stroke. This shows that this field of research is quite challenging and is open to new research into techniques of detection and segmentation in non-contrasted enhanced CT images.

Most stroke detection works using CT images focus on only one type of lesion. In an attempt to overcome this situation [36] developed a detection system using Convolutional Neural Networks (CNN) optimized with Particle Swarm Optimization (PSO). Only a few studies have used nature-based and metaheuristic-based techniques to optimize CNNs, dealing only with CNN parameters (i.e., weights and biases), not with their hyper-parameters (i.e., learning rate, momentum, and decay of weight). In addition to these contributions, the authors provided a database of CT images composed of 25 exams generated using a GE Medical System HiSpeed tomography, that were obtained with the support of Trajano Almeida Clinic - Diagnostic Imaging, Fortaleza-CE, Brazil. Some images were discarded due to poor quality, resulting in 300 images, composed of 100 normal images and 200 with stroke (100 hemorrhagic and 100 ischemic) that contained non-regular patterns, irregular lighting and different structural characteristics. The experiments were performed with the ImageNet and CIFAR-10 architectures and the database split (training/testing) of 50/50 and 75/25, respectively. Experiments with the 75/25 protocol and CIFAR-10 architecture obtained the best accuracy results, near to $98,86 \pm 0,65$. An important result of this approach was the correct classification of patients with stroke, that is, no ischemic patient was classified as healthy or hemorrhagic. Considering the healthy individuals, only a few were classified as hemorrhagic patients. However some of the hemorrhagic patients were classified as ischemic, but no hemorrhagic patient was classified as healthy. However, the authors intend to find other alternatives to improve the results, including by increasing the databases and testing different deep learning techniques, such as Deep Belief Networks. The authors state that this work can serve as a basis for other research work, since the dataset projected in this article is now publicly available. Only two papers used MRI scans for stroke detection. [37] used MRI images to detect stroke and in this work evaluated the performance of k-nearest neighbor (kNN) and minimum mean distance (MMD) classifiers to identify hemorrhagic strokes. The classifiers were tested in a database composed of 50 MRI images of different patients, with three configurations of distance metrics: Euclidean, Sum and Maximal. The results showed that the kNN surpassed the MMD in the detection and quantification of the area of hemorrhagic strokes and that the best distance metric for the two classifiers is the maximal distance. In [38], the authors proposed a method that combines the advantages of unsupervised and supervised methods. Specifically, the unsupervised component detects the injured hemisphere, performs an enantiomorphic normalization[2] and constructs a Lesion Probability Map (LPM) using a Fuzzy Clustering Pipeline (FCP). The LPMs are then used to construct a high-dimensional voxel-based vector of features which provides anatomical/spatial information increasing the discrimination between the lesion and healthy tissues. The supervised component used the features vector to train a combination of support vector

[2]**Enantiomorphism** or **Enantiomorphic image**: the existence of two chemically identical crystal form as mirror images of each other.

machine (SVM) classifiers for the final detection of the lesion. To validate the proposed system, the authors tested the method using 60 MRI scans of different patients. Using cross-validation leave-one-out, the proposed method reached an average dice similarity coefficient (DSC) of 73.1% when compared to the manual approaches of trained neurologists. In addition, they tested with the BRCA-2012 MICCAI dataset attaining an average DSC of 66.5%. Also, with these two sets of test data, the proposed method showed competitive performance when compared with three state-of-art methods ([39]–[41]). The identification and analysis of brain lesions resulting from a stroke can help to understand the relationship between lesion and deficit, predict the diagnosis and prognosis of the patient and trace the development of the cerebral pathology over time.

Standard exams to diagnose stroke are CT and MRI, but for some developing countries the availability is very limited and relatively expensive. An alternative to these tests is presented by [42], who developed a study using a genetic algorithm and k-nearest neighbors (GA/kNN) to optimize the identification of a pattern of genetic expression in the peripheral blood in order to accelerate the ischemic stroke diagnosis. A cohort analysis of 39 patients with stroke and 24 neurologically asymptomatic patients (control) was performed from peripheral blood samples using the microarray technology of patients who were admitted to the Ruby Memorial Hospital in Morgantown, WV, USA. The expression pattern was evaluated via qRT-PCR[3] in a validation group, where the algorithm ability to discriminate between an 39 patients with stroke and 30 of control, as well as 20 stroke mimics were tested. GA/kNN identified 10 genes whose coordinate pattern of expression was able to correctly identify 98.4 % of the cohort individuals. In the validation cohort, expression levels of the same 10 genes were able to correctly identify 95.6% of subjects when compared to patients with asymptomatic control and 94.9% as compared to patients with ischemic stroke mimics. The transcriptional pattern identified in this study shows a strong diagnostic potential and deserves further evaluation to determine its true clinical efficacy. Another alternative is the use of electroencephalography (EEG), since a person with ischemic stroke has a reduction in cerebral blood flow which makes the EEG signal decelerate. [43] developed a new technique to recognize the ischemic stroke from the EEG signal and electrooculogram (EOG) using a Deep Learning approach. A 1D CNN is used to distinguish EEG and EOG data from patients with signs of ischemic stroke. The EEG and EOG data used in the tests were recorded by the National Brain Center Hospital, Jakarta, Indonesia. The data are from 32 patients with stroke and 30 normal patients acquired on two different machines, the Xltek with a sampling rate of 512 Hz, and Biologic with a rate of 512 Hz and 256 Hz. Signals were recorded on 33 channels, but only 2 EEG channels (C3 and OZ) and 2 EOG channels (left and right) were used. The CNN 1D was compared with the Naive Bayes, kNN, Random Forest, Classification Tree, Neural Net and Logistic Regression classifiers. The experiments were performed on a Linux platform for 1DCNN implementation and windows for the other classifiers. The hardware consisted of a quad core i7 cpu of 2.4 GHz with 4 GB of RAM. The 1DCNN were evaluated with 100 and 200 epochs. From the general evaluation parameters, the 1DCNN (both of 100 epoch and 200 epoch) obtained better results than the others, and the configuration with 200 epoch had the best values of accuracy, sensitivity, specificity, F-Score, precision and recall, above 0.86. Comparing the results with the second best classifier, Naive Bayes, the 1DCNN was about 16.8% superior. The results confirm that the EEG and EOG examination has a great potential and possibility to distinguish a person with stroke from a healthy person.

Microwave imaging has been used for years to detect of breast tumors. Recently, the detection and location of stroke in microwave images (MWI) has been considered a challenging application. The use of microwave imaging to estimate the dielectric characteristics of cerebral parenchyma has attracted the attention of several researchers. Non-ionizing radiation, unlike CT and MRI, and has a low set-up which makes this technique suitable for use in clinical medicine for stroke diagnosis. On the other hand, processing the spread signal for reliable diagnoses in a human head is a very challenging task. [44] presented a method to detect of hemorrhagic strokes in MWI. This method is based on the Gauss-Newton algorithm and was used due to its effectiveness in dealing with the non-linearity and misalignment of the inverse dispersion problem, which is the mathematical basis of imaging techniques. The approach is based on the maps of the dielectric parameters of cerebral parenchyma that are obtained by inverting the integral equations of the inverse scattering problem. The system consists of a set of 36 antennas equally distributed over a 0.11 m radius operating at 1 GHz. Each antenna, acts as a transmitter, while all others are used to collect the electric field around the head. The results show the efficiency of the approach in discriminating regions of the stroke and healthy tissues. Although preliminary, these results are promissory. Moreover there is the added possibility of developing small and low-cost diagnostic devices for this method that can be transported in ambulances and other medical vehicles. Besides, since it is based on non-ionizing radiation, it is safe for patients and operators. MWI systems are low cost and have portability, which has aroused interest of researchers in the field of medical diagnosis. [45] developed an ultra-miniaturized band antenna with dimensions of $40 \times 40 \times 0.6$ mm^3 with a return loss of $S_{11} < -10$ bB and a working frequency of 1 GHz at 4 GHz. The antenna was applied to a stroke detection experiment in a simplified brain model. The system of detection and location of stroke is based on the premise that there is an obvious difference in the dielectric constant (ϵ) between the area affected by the stroke and the normal area. The antenna is implanted around the object under test (OUT) and connected to the vector network analyzer (VNA). The VNA is controlled by a computer connected to a remote workstation and performs the following process: the antenna radiates a signal to the OUT, then the different dielectric constant area within the OUT produces a spread signal with different phase and amplitude characteristics and the reflection coefficient is recorded in the VNA. The reflection coefficient is analyzed to calculate the position of

[3]**Quantitative real-time reverse transcription polymerase chain reaction (qRT-PCR):** is a laboratory technique based on the principle of polymerase chain reaction (PCR) to multiply nucleic acids and quantification of DNA.

the dielectric constant variation using the Confocal algorithm. Although, the system has achieved promising results, however it still requires some tests on more accurate head models and real patients in order to confirm its effectiveness. In another paper, [46] proposed a modified elliptical monopolar antenna with two slots and two high-pass filters (HPF), with dimensions $150 \times 75 \times 1$ mm and made on FR4 (flame retardant) substrate ($\epsilon_r = 4$) for stroke localization. The propagation pulse fidelity was simulated with Computer Simulation Technology (CST) Microwave Studio software. The brain was modeled as a flat 4-layer phantom consisting of 2 mm of skin, 10 mm of bone, 200 mm of white matter and 200 mm of gray matter. The cerebral phantom is located 40 mm from the edge of the antenna and 21 field probes E, which measure the propagation signal, are positioned along the Y axis at 20 mm intervals. In the simulation, two different pulses are excited, one contains broadband and low frequency (0.5 GHz to 0.55 GHz) and the other does not contain the low frequency band. The simulation results confirmed that the location of the stroke requires broadband pulse and low frequency. The simulations also showed that the normalized fidelities and amplitudes of the E field are similar for both cases. However, the normalized fidelity and amplitude of the E field of the signal without low frequency drops faster than those with low frequency signal. The authors conclude that the proposed antenna is a good candidate for a stroke localization device.

In order to increase the recovery rate further and reduce the consequences of a stroke, continuous post-event monitoring of physiological parameters in the acute phase has been gaining importance. [47] used the technique of compressive sensing as an imaging tool for the generation of MWI to aid in the monitoring of the stroke. In order to detect and monitor the progress of a stroke, they used data from several time-separated measurements. Differences in the electromagnetic field indicate changes in electromagnetic properties due to the stroke. Although the changes are small and confined to a particular region, compressive detection produces accurate images with high resolution. An ideal case was used to serve as reference where the data was not noise-free and prior knowledge showed that the electromagnetic parameters of the head (besides the stroke) was perfect. The validation tests occurred in a realistic non-homogeneous numerical model. Although prior knowledge of head parameters was very limited, stroke reconstructions were similar to those obtained in the ideal case. The relevance of this approach was the robustness of sparse processing against errors in prior knowledge of the electromagnetic properties of the brain. The results obtained were promising, demonstrating a significant potential of the compressive sensing technique in solving similar problems.

However, brain MWI impose some challenges. An example is the presence of scalp that generates intense artifacts for the backscatter signals. Most of the works that use MWI for stroke detection focus on the antenna design or anatomical models and not in the backscatter signal processing algorithms. The authors in [48] used radar images of Ultra-Wide Band (UWB) to detect stroke and backscatter signal processing algorithms. The authors proposed and compared two algorithms of artifact removal. The first was the beamforming Microwave Imaging Space Time (MIST) modification which was proposed by Hagness [49]. The second was the Partial Least Square Regression (PLSR) algorithm that use an approach based on statistical methods. The effectiveness of the two algorithms was compared in terms of localization accuracy, quantity of false positives and computational complexity. The results showed that the proposed artifact removal algorithms were fundamental to increase the performance not only in terms of localization accuracy but also in the reduction of false positives. The PLSR approach had better performance and less computational complexity. The main conclusion of this research was that the statistical approach for artifact removal represents an attractive solution in terms of accuracy as well as complexity. This could encourage the investigation of statistical approaches for the artifact removal, using the Principal Component Analysis (PCA).

[50] proposed a methodology based on learning-by-examples for real time stroke detection using from measures of microwave dispersion. The problem was formulated as a binary classification and used a SVM classifier. During the training, a database of I/O (i.e., presence of stroke in a known location vs scattering data collected by an array of antennas) is generated to construct a decision function and, then, used during the test stage to make real-time predictions. A simplified, but realistic, phantom head model with the shape of octagonal prism with compatible dimensions to a human head and filled with a liquid mixture to emulate the electromagnetic behavior of brain tissue was used for the experimental validation. The stroke region was modeled in a circular cylinder with 40 mm diameter and height of 200 mm and filled with a liquid that simulated the stroke dielectric characteristics. The model was surrounded by 8 bow-tie antennas printed on a Rogers Duroid 4003C substrate of 1.5 mm thickness. The proposal was compared with experimental data collected in the ELEDIA CTU laboratories, Technical University of Czech Republic, Prague, Czech Republic. The results showed that the accuracy quickly improves as new samples are added to the training set. With a training set of $N \leq 50$, the method achieved 100% accuracy (ACC) and 0% error. However, the study lacks experiments with real people and with different stroke types.

[51] developed a new technique for the stroke detection through MWI subspatial pattern recognition. The system has stages of individual bases constructed for each class and calculates the dot product of the test vector. A classifier called Naive Inner-product Subspace Classifier (ISC) was used as the basic classification model, where a base for each subspace is estimated using a Singular Value Decomposition (SVD) from the training data. Because data from both classes share many parameters, the reduced sized subspaces for each class are formed by removing some close directions in the subspace, which improve the class separability. In this paper, they used the S21 and the intersection of two antennas (one receptor and one transmitter) to obtain the diffuse positioning. The results showed that the systems can differentiate the patient with stroke and detect the position of blood clots by using the line between the two antennas. The results of the evaluation with the finite difference time domain (FDTD) method showed that the proposed technique

can detect and locate blood clots efficiently. Thus, according to the authors, a portable MWI device can be developed for mobile medical applications.

In [52], the authors researched the difference in the dielectric properties between healthy brain tissues and stroke tissues. The paper illustrated the project and the set-up was with a planar spiral antenna manufactured with RO4350B, 1.524 mm thick, with a relative permittivity of 3.66, loss tangent of 0.04 S / m and running at 426.6 MHz. The antenna was tested in normal human head models and with stroke models using the CST Microwave Studio, and posteriorly was tested on human heads. The system detects a frequency displacement of 200 to 800 KHz between normal people and people with stroke. In another research, [53] designed a UWB pentagon antenna operating in a range from 3.3568 to 12.604 GHz with a size of 44×30 mm^2 and 1.5 mm thick. The project was also tested in the CST Microwave Studio and in a human head model with stroke. The authors reported that there is a frequency displacement of 213 MHz between the normal head model and the simulation with tumor and a frequency displacement of 218 MHz in the simulation of the stroke head model. According to the results of both projects, there is a close similarity between the measured and simulated values. The main interest in the use of MWI for stroke detection is in the fact that this technology combines two advantages: it generates the image quickly and is portable. This makes it possible to use such a device in ambulances.

The comparison between the papers in this subsection is summarized in Table I.

B. Stroke Segmentation

An analysis of the extension of the stroke in each exam slice is important for the diagnostic and treatment definition for each patient. The actual pattern for this process is manual segmentation, which makes the process time-consuming and susceptible to human error. Automatic stroke segmentation methods delineate the injured region without human intervention.

[54] analyzed the semi automatic segmentation process of the Clusterize algorithm [55] in CT exams and MRI patients with ischemic stroke. The results were compared with the manual segmentation realized by a specialist, in relation to the final map of the lesion, processing time and interobserver reliability. The database used in the test was composed of 44 images (13 of CT, 16 of MRI-DWI and 15 of MRI-T2FLAIR) from the Tubingen Neurology Center, Germany. The algorithm was integrated in a statistical parametric mapping toolbox and used in the SPM8 in MatlabR2013b. The values of DSC ($\leq$0.87) and Jaccard's coefficient (JAC) ($\leq$0.77) show that the agreement between the lesion maps was excellent, suggesting that the accuracy of the Clusterize is comparable to the Ground Truth. The semi automated approach still allows a human quality control strategy not implemented in totally automated methods, avoiding the perpetuation of errors from posterior analyses.

[56] developed a CAD system for the automatic stroke segmentation from CT images. The system is composed of a radial function neural network (RBFNN) and uses the multi objective genetic algorithm (MOGA) to determine the classifier structure and its input parameters, minimizing the number of false positives, maximizing the accuracy while ensuring generalization and reducing the model complexity. Posteriorly, [57] and [58] introduced information about the brain asymmetry with another 51 statistical characteristics such as the RBFNN input, increasing the performance of the method. These authors used their own database for the validation experiments. The base is composed of 7 brain CT scans divided into 150 slices obtained from the same equipment. After the use of the MOGA two models were selected, Experiment 1 and 2, and the networks were trained and applied to the database. The best results was obtained from Experiment 2, with a specificity (SPC) of 98.01% (i.e., 1.99% of false positives) and a sensibility (TPR) of 98.22% (i.e., 1.78% of false negatives) when compared with the ground truth marked by a neuro-radiologist. This approach was also compared with other 3 publications, surpassing them in terms of specificity, accuracy and precision. Although the classifier has the capability to detect most lesions, sometimes it identify false lesions, and this is the principal problem to be overcome. Besides, the classifier is limited to a single type of lesion.

[59] developed a CAD system to detect, segment and quantify hemorrhagic strokes in CT images without brain contrast. The system segments the brain regions and then computes the attributes: total skull volume, brain tissue, cerebrospinal fluid (CSF) ratio of blood volume/total skull volume and total CSF volume/cranial volume. In order to increase the accuracy in the quantification of the markers, a graphic user interface which allows a visual examination of the segmentation results and the possibility to correct potential errors, was used. The system was applied to a database composed of 96 CT scans where the average patient age was over 50 years old. The system uses the region growing algorithm with an adaptively adjustable threshold to segment the brain region. Then, it uses a thresholding algorithm to detect the normal brain tissue, blood and the CSF. The attributes of the brain volume are extracted from the results of the segmentation. Results were visually examined, demonstrating computational efficiency in automatic segmentation with relatively high accuracy, as well as providing interactive functions for corrections. Although the image quality varies widely among the dataset, the CAD system is able to process such images adaptively and produce satisfactory results. The preliminary feedback from the researchers is encouraging, indicating that this new CAD tool is easy to use compared to other automated black box-type tools. The authors plan to expand the database to include more than 300 patients with hemorrhagic stroke and conduct a detailed study of the statistical data to evaluate the association between these markers based on the image and the prognosis of the patients.

The quality of CT images may be affected by the lack of homogeneity of X-ray intensity during the examinations, which causes difficulties in the detection of cerebral hemorrhages. Therefore, [60] performed a comparative analysis of thresholding, region growing, fuzzy clustering and active contour-based techniques in the stroke segmentation process. The results of these methods are compared with the ground truth manually delineated by a specialist. The database used consisted of 10 CT images generated by a tomograph (GE Medical Systems)

TABLE I
LIST OF STROKE DETECTION

Study	**ST**	TE	D	M	Tec	Auto
Inoue et al. [34] Iyama et al. [15]	i	CT	Pv	ROC, Jack Knife	IRM-Neuro, FBP	A
Gomolka et al. [35]	i	CT-NC	Pv	Quantitative	HU scale	A
Pereira et al. [36]	i and h	CT	Pu	ACC, Confusion Matrix	CNN+ PSO	A
Sudharani et al. [37]	h	IRM	Pv	Quantitative	k-NN, MMD	A
Guo et al. [38]	i	3D-MRI-T1	Pv	DSC	FCP + SVM	A
O'Connell et al. [42]	i	Bloond	Pv	IBM SPSS Statistics	GA/kNN	A
Giri et al. [43]	i	EEG and EOG	Pv	Comparative, ACC, SPC, TPR, F-Score	1DCNN	A
Wu et al. [45]	i and h	Microwave	Pv	Computational Simulation	Confocal Algorithm	A
Bisio et al. [44]	h	Microwave	Pv	Experimental	Gauss-Newton Algorithm	A
Stevanovic et al. [47]	i and h	Microwave	Pv	Electromagnetic parameters and Green's functions	CS	A
Lee et al. [46]	i and h	Microwave	Pv	Computational Simulator	Antenna Slot and HPF	A
Ricci et al. [48]	i and h	Microwave	Pv	FP	MIST	A
Salucci et al. [50]	i and h	Microwave	Pv	ACC, error	LBE, SVM	A
Wu et al. [51]	i and h	Microwave	Pv	FDTD	Naive ISCV, SVD	A
Shokry & Allam [52] Shokry & Allam [53]	i and h	Microwave	Pv	Simulator CST Studio	Antenna PSA	A

The **ST** column indicates the stroke type, (i) ischemic and (h) hemorrhagic. **TE** indicates the type of exam. **D** indicates if the database is public (Pu) or private (Pv). **M** indicates the evaluation metrics. **Tec** indicates the technology used. And **Auto** indicates the automation level, (A) automatic, (S) semi-automatic or (M) manual.

configured with a 25 × 25 cm field of view, 120 kV peak voltage, 100 mA tube current and dimensions 512 × 512 × 3 mm and 10 mm of space between slices. The accuracy, sensitivity, specificity and overlap metrics were calculated for the comparative analyses. The results showed that the active contour-based method is superior to other approaches in terms of accuracy. All the above methods are fully or partially manual and their performances depend on human expertise. Thus, the development of automatic segmentation methods for stroke detection has a promissory future.

[61] proposed a new 3D hemorrhagic stroke segmentation method in CT scans of the brain. The segmentation is carried out with the supervoxel algorithm based on simple linear iterative clustering (SLIC) and refined with the graph algorithm. The method performs a pre-processing step by applying the Fuzzy C-mean (FCM) algorithm for skull removal and Otsu's adaptive thresholding to segment the hemorrhagic region. Then, the location of the hemorrhagic region is determined accurately with the reconstruction of a series of 2D images in 3D spaces using rendering techniques. The experiments were performed with a database consisting of 20 exams (250 to 350 CT 2D images) of patients with intracranial hemorrhage, from the Department of Neurosurgery, CPLA No. 98 Hospital, Huzhou, China. The images were acquired with a General Electric (GE) scanner in Digital Imaging and Communications in Medicine (DICOM) format, with a size of 512 × 512 and spatial resolution of 0.488 × 0.468 mm. The results were compared to the ground truth and other five 2D segmentation methods: CV model method, Snakes model, Graph cuts for 2D images, SLIC + graph cuts for 2D images and SLIC superpixel algorithm. The results highlighted the prominence of the SLIC + graph cuts for 2D images and the proposed method. The proposed method obtained a True Positive Fraction (TPF) of 97.94 %, False Fraction (FF) of 92.26 % and the second best execution time. Experimental results demonstrated that the proposed approach provides segmentation that is similar to the manually labeled ground truth and outperforms existing 2D methods in accuracy and time. The contribution of this work was to design the graph cuts energy function to meet the specific problem of 3D supervoxel segmentation.

[62] developed a new Level Set approach for hemorrhagic stroke segmentation of CT images based on the likelihood of Normal distribution. The method called Level Set Based on Analysis of Brain Radiological Densities (LSBRD) adds as a contribution the analysis of intervals of pixel intensities in grayscale images. The authors adopted 80 HU for the window width and 40 HU for the central level and proposed an optimum initialization of the Level Set, where level zero is determined by the analysis of the radiological densities of the brain tissue. These level adjustments make stroke segmentation more efficient. The proposed method was compared to the Level Set algorithm based on Coherent Propagation Method (LSCPM), Watershed and Region Growing. These were applied to a database composed of 100 exams acquired with a GE Medical System Hi-Speed CT scanner at the Heart Hospital of Fortaleza, Brazil. The results were compared with the ground truth manually segmented by a medical specialist. The proposed method was comparatively more stable, and obtained an average ACC of 99.83% and a F-Score higher than 92%. The tests were performed on a 2.4 GHz Intel Core i5 processor with 8 GB of RAM, using MATLAB. In terms of segmentation time (in seconds), the LSDRD method targeted 1.76 ± 0.29 s and other methods have their segmentation time superior to 3 seconds. LSCPM consumed 4.81 ± 1.18 s. These data indicate that the LSDRD method is superior to other methods and therefore a promising methodology that can be used in routine clinical diagnoses Also it has a good time of execution, and is a competitive method for equipment in clinical use today.

The first signs of cerebral ischemia are subtle and difficult to identify visually on CT images. To overcome this adversity [63] proposed a detection method based on increasing the contrast in the images. The approach aims to solve this difficulty by improving the contrast on several scales based on the Laplacian Pyramid (LP) and Fuzzy-C means classifier to extract the ischemic area from the normal tissue. In order to evaluate the method, the results of the proposed method were compared with the results of the discrete wavelet transform (DWT). The proposed method obtained the best results, besides presenting an average processing time of 10.46 s. The aim of the study was to improve the differentiation of the brain pathology area (hypodense) from its adjacent normal parenchyma. Making the extraction of the ischemic zone shortly after the first signs of an ischemic stroke, in order to help specialists to diagnose and determine the best treatment. However, the experimental results showed that the proposed method is more appropriate for small ischemic strokes. In the case of large or multiple lesions in both hemispheres, the algorithm does not give satisfactory results because the size of the improved details depends on the number of decomposition levels. If the number of decomposition levels increases, the appearance of the image is affected.

Algorithms for ischemic stroke segmentation in MRI scans are have intensively researched, but the reported results until now do not allow a comparative analysis due to the use of different databases and validation schemes. Among the analyzed papers, the paper by [64] addressed this problem with the Ischemic Stroke Lesion Segmentation challenge (ISLES) organized in conjunction with the Medical Image Computing and Computer Assisted Intervention (MICCAI'15) conference. With ISLES, an evaluation framework is provided for the comparison of the algorithms. A set of publicly available data is described in detail and as well as the results of the two subchallenges: Subacute Stroke Injury Segmentation (SISS) and Spill Perfusion Estimate (SPES). The SISS consisted of a database of 64 cases of ischemic stroke in MRI scans separated into T1, T2, T2FLAIR and DWI. These scans were provided by the Schleswig-Holstein University Medical Center in Lübeck and the Department of Neuroradiology at the Klinikum rechts der Isar in Munich, Germany. Both centers are equipped with Phillips 3T systems. The SPES database contained the MRI exams of patients with ischemic stroke treated at the University Hospital of Bern-Switzerland between 2005 and 2013. MRI images were obtained on a 1.5 T system (Siemens Magnetom Avanto) or 3T MRI (Siemens Magnetom Trio). A total of 16 research groups participated with 21 automatic segmentation algorithms. After an analysis of the results, a critical evaluation of the current state of the art, recommendations for future developments and the identification of the remaining challenges were made possible. In summary, no algorithm performed better than the others, but approaches using combinations of multiple methods and/or domain knowledge performed relatively well. The segmentation of lesions in SPES was considered viable. However, the algorithms applied to the segmentation of lesions in the SISS still lack accuracy. A valuable addition to ISLES would be a similarly organized reference, based on data from CT images, allowing a direct comparison between the modalities and the information they would be able to provide to the segmentation algorithms. Annotated ISLES image datasets remain publicly available through an online assessment system to serve as an ongoing benchmarking feature. In another survey, [65] evaluated and compared nine classification approaches in one direct comparison using an MRI database of publicly available ischemic stroke patients. This analysis included the k-NN and Gaussian Naive Bayes (GNB), Generalized Linear Models (GLM), Random Decision Forests (RDF) and CNN methods. The results brought improvements to the segmentation problem and provided a solid foundation for the development of more specialized solutions. The evaluation included a juxtaposition of mono- and multi-spectral MRI datasets and took the inter observer variability into account. The evaluation was performed using the Dice Similarity Coefficient (DM), the average symmetric surface distance (ASSD) and Hausdorff distance (HD). In addition, the precision and recall values were reported for each classifier to evaluate over and under segmentation, respectively. The quantitative results for Extra Tree (ET), RDF and CNN, were superior in comparison to all results previously reported in the literature. However, it should be noted that these comparisons are not really valid, since different databases and different ground truths were used for the evaluations. Unfortunately, there were no publicly available datasets to compare the ischemic stroke segmentation methods before 2015.

The curvelet transform is a new and effective spectral transform that has been widely used in the digital image processing (DIP) and pattern recognition (PR) fields. [66] developed an extensive study on the use of this transform for ischemic stroke characterization in MRI images. In the article, the curvelet analysis was applied to the region of interest at different scales and along multiple directions. The database used consisted of 45 axial MRI exams, in which 20 were abnormal and 25 were healthy. The database was from the PBM hospitals, Rajasthan and Global Health City, Chennai. The images were in the DICOM format and voxel resolution was $1 \times 0.5 \times 0.5$ mm. The characteristic vector was used as an input of an SVM that discriminates normal and abnormal tissues. The authors tested four different kernel functions, and obtained the best results with the RBF kernel. To evaluate the approach, the ACC, TPR and SPC were calculated and the results were compared with the gray-level co-occurrence matrix (GLCM) and Wavelet methods. The curvelet method obtained a mean ACC above 98.8% with precision (PPV) of 99.1%, in addition to high TPR and SPC rates. The results show that the curvelet is as accurate or superior to the methods compared. However, the authors recognize the need to validate the results using a larger dataset and compare them with more techniques. [67] presented a new method of supervised learning for automatic segmentation of MRI-T1 lesions aiming to overcome the possible subjective biases of the manual ischemic stroke segmentation process. The method used the Naive Bayes classifier to identify lesion voxels from unified normalization using the New Segment tool implemented with Statistical Parametric Mapping (SPM) to obtain probabilistic maps of brain tissues and to estimate the probability of brain tissue, gray matter (GM), white matter (WM), CSF, and not cerebral. The database used in the tests consisted of 30 MRI-T1 exams of patients with hemispheric ischemic stroke that had occurred at least 6 months previously. The examinations were conducted with high resolution equipment specifically used for research at Cincinnati Children's Hospital Medical Center (CCHMC) and the University of Alabama in Birmingham. The method was validated by comparing it to manual segmentation performed by a neurologist. The results indicated that the method is capable of generating high quality masks of lesions for patients with different stroke sizes, forms and in different regions. The method was sensitive to indirect lesions that may be difficult to detect by visual inspection on a MRI-T1, and even identified the direct effects of the lesion that were lost during manual delineation. Overall the method performed well; however, in some cases, it returned several false positives, possibly, due to the location and the size of the lesion. The results are encouraging, but the authors emphasized that the method is not intended to detect lesions with very small extensions, such as those occurring in multiple sclerosis or Alzheimer's disease. [68] hypothesized that the apparent diffusion coefficient (ADC) could provide a good imaging marker to identify the ischemic nucleus in patients with acute stroke. They then developed a study to determine the optimal ADC threshold to be implemented in a fully automated ischemic core identification software. The database used in the tests consisted of a sequential MRI dataset obtained prospectively as part of the Diffusion and Perfusion Imaging Evaluation for Understanding Stroke Evolution (DEFUSE) study. The threshold was identified by ROC analysis in each subject. Finally, data from all participants were grouped and Youden's index, which weighs sensitivity and specificity equally, was maximized to determine the ideal threshold. The results showed that the ADC threshold can be used in acute stroke to delineate the ischemic nucleus with reasonable TPR and SPC. This provides the basis for software development that can quickly and objectively delineate the ischemic nucleus without manual intervention. [69] developed a new approach for automatic segmentation based on Extra Tree (ET) forests. The method consists of a pre-processing where voxel-wise attributes are extracted from a sequence of MRI exams, which are then used in ET training. The main objective is to use a ML method to try to capture the complex and non-linear class boundaries in the resource space that allow to separate the lesion voxels from voxels without injury. The validation tests were performed on a database of MRI-T1w, T2w, FLAIR and DWI MRI exams, which were used in three clinical studies ([70]–[72]). The MRI were acquired using a PHILLIPS 3T Achieva 3.0T TX scanner during routine clinical care in Amsterdam. The Netherlands Statistical analysis indicated that the method was largely independent on clinical and anatomical parameters of stroke, except for image quality. Among the MRI sequences in FLAIR, the method obtained a better segmentation of subacute lesions of ischemic stroke, although the method was also effective in other modalities. However, in two cases, the approach did not detect stroke injury and, in some cases, the quality of segmentation was poor, but most of these cases the lack of effectiveness was attributed to the low quality FLAIR image. In the future, the authors intend to test more elaborate resources to support the discrimination process and employ subsequent narrowband segmentation to combat sub segmentation.

Different regions of a lesion may have different contrast properties in different types of medical images, which makes it difficult to automate the segmentation process. [73] used the Active Learning selective sampling strategy to train the Random Forest (RF) classifier in order to optimize the voxel-based ischemic stroke segmentation in different types of MRI. The proposed method performs a preprocessing to construct the characteristic vector, composed of data specific to each exam such as MRI, functional MRI (fMRI) and Diffusion Weighted Imaging (DWI). The classifier was then trained using a small training set that improves with informative samples from each iteration. Each step involved retraining the classifier and testing the remaining data to obtain the evolution of classification accuracy. Four segmentation experiments, each with a different ground truth, were performed in different MRI modalities. The segmentation was repeated ten times in each experiment and the mean evolution and standard deviation data of the accuracy, sensitivity and specificity of the classification were computed for each iteration. The results were encouraging, as sensitivity of over 90% was reached in some cases. The variability of the results decreased with each iteration of the active learning process so that good results are expected in any situation because the learning process will correct any deviation from the optimal results. [74] used the Fuzzy C-Means Clustering technique with a multidimensional approach to segment brain tissues with lesions and morphological processing to extract the ischemic stroke lesions from MRI-DWI exams. The database used for testing consisted of four slices of different patient exams that presented a well-defined beginning time of symptoms, absence of cerebral hemorrhage, and visually apparent lesion. The examinations were performed on a 1.5 T MRI scanner (GE-OPTIMA MR 360) at the IMS Hospital & SUM (Bhubaneswar, India). The main contribution of this process was to detect the acute injury of the ischemic stroke and to measure the relative area of the lesion in relation to the total area of the brain. The results show that multidimensional Fuzzy C-Means Clustering has great potential for detection, segmentation, localization and measurement of ischemic stroke volumes. However, further improvements are needed to validate the results in addition to applying a larger and more variable injury database to prove the effectiveness of the approach. The exact location of the stroke injury is an essential part of the diagnosis and treatment planning. However, the various forms of injury make this task complex and challenging. [75] proposed a new method for stroke lesions segmentations MRI-DWI images. The method performs a preprocessing with the fuzzy enhancement operator and uses the gaussian mixture model (GMM) to localize the lesion area and segment the brain regiment into two classes (stroke and normal). In order to eliminate erroneously classified pixels representing the false detection of the infarct region, the operator of the binary morphological area is applied to eliminate the connected components based on their area (number of pixels) which must be smaller than a specified limit (200 to 300 pixels). The method was applied using a multicenter database composed of 50 MRI-DWI slices obtained from two scanners with the same power but different configurations. Thirty images were taken using a GE Signa 1.5-T SYS-GEMSOW and the others were obtained with a Philips Achieva 1.5-T. The code was implemented in MATLAB 2014a, and the entire experiment was performed on an Intel Core ^{TM} i5 processor with 4 GB RAM. The ground truth was segmented by two experts. The dispersion plot between the lesion area detected by the proposed method and the first specialist obtained a regression value of 0.98 and, the other expert obtained 0.99. Experimentally, the proposed technique provided satisfactory performance on the database and its results were comparable with other existing methods. The statistical significance of the results justifies its efficiency and use in a CAD system for segmentation of ischemic stroke in MRI-DWI.

[76] proposed a new automatic stroke segmentation method in MRI-DWI images using fully convolutional and densely connected 3D neural networks (3D-FC-DenseNet). The method efficiently uses contextual information to learn discriminative characteristics in an end-to-end and data-driven manner. To minimize training costs, due to its dense connectivity, 3D FC-DenseNet allows the unimpeded spread of information and gradients across the network. The method was validated using a database composed of 242 exams (90 for training, 62 for validation and 90 for tests) and these included several types of ischemic stroke. The exams were acquired using two scanners, 128 were obtained from a 1.5-T scanner (Sonata, Siemens Medical, Erlangen, Germany) and 114 from a 3.0-T scanner (Achieva 3.0 T-Series; Philips Medical System, Best, The Netherlands). The dataset was labeled by an experienced neurologist (Dr. Wenyan Liu), and was verified by another experienced assessor (Dr. Lei Zhao). To further demonstrate the effectiveness of the proposed segmentation algorithm, the authors evaluated the model in a public dataset, i.e., ISLES2015-SSIS. They also performed a comparative analysis with two types of 3D CNN of the latest generation in the field of medical image analysis (MIA). The method was implemented with a PyTorch Framework in Python 3.6 on a PC with 16 GB RAM, an Intel Core i7-4790 CPU 3.60 GHz and an NVIDIA TITAN X GPU. The results showed a high performance in several metrics (Dice similarity coefficient: 79.13%, lesionwise precision: 92.67% and lesionwise F1 score: 89.25%), surpassing the other methods by a wide margin. The authors performed extensive comparative tests on private databases and datasets of public challenges and the results corroborated the superiority of the proposed method. Due to its fast, accurate and robust performance, the method has good potential in clinical practice and can serve as a preliminary step in a CAD system. [77] proposed a system composed of two networks, one is an ensemble of two DeconvNets, which is the EDD Net; the second CNN is the multi-scale convolutional label evaluation net (MUSCLE Net) Net. The EDD Network is a set of two DeconvNets ([78]) and the MUSCLE Net is a Multi-Scale Convolutional Label Evaluation Net. The EDD Network first produces a probability map of primary segmentation. The binary segmentation obtained by the probability map threshold contains both lesions and several false positives (FP), then MUSCLE Net re-evaluates all detections by EDD Net and excludes many FPs using the probability map and the original input image. The authors state that this is the first attempt to solve this problem using this structure of CNNs. They analyzed the network architectures and the main settings in detail to ensure the best performance. It was validated using a database of 741 MRI-DWI exams of acute stroke patients from local hospitals. All clinical images were collected from a retrospective database and anonymized before use by the researchers. The scans were obtained from three different scanners (Siemens) with the field intensities of 1.5 T and 3 T. The acute ischemic lesions were delineated by experienced specialists in all images. The training database contained 380 scans and the remaining 361 were used for testing purposes only. The configuration gave very good results, with a DSC of 0.67. The mean Dice scores for small and large lesions were 0.61 and 0.83, respectively. The injury detection rate achieved was 94%. Although the combination of EDD + MUSCLE Nets achieved very good results, the proposed approach still has some limitations: first, the semantic segmentation of objects in images at multiple scales remains a challenge that is not solved fundamentally. Second, training and testing are not end-to-end, which lowers system efficiency. Finally, in the second stage, only false positives were considered. Besides, there are still a small number of false negatives that need to be corrected.

[79] developed an automatic stroke lesion segmentation in MRI images. The Lesion Identification with Neighborhood Data Analysis (LINDA) system aims to address the deficiency of manual tracking by performing hierarchical improvements to estimate the lesion from low to high resolution considering both the signal in the voxel itself and the neighbors. The neighborhood voxels allow the algorithm to learn rules based on the surrounding environment, a skill needed to perform conditional targeting. In order to investigate the accumulation of automatic prediction errors and the impact on hypothesis testing, a comparative analysis was performed between lesion-to-symptom mapping (LSM) of voxel maps obtained from manual segmentation with those obtained from the LINDA. The database used was composed of 60 medical images of patients with left hemispheric stroke. Comparative tests resulted in similar neurocognitive maps, although with some discrepancies. The LSM with LINDA was more robust to the LSM voxel prediction error. The results showed that, although there are several limitations, the values achieved compete or exceed the state of the art methods, producing consistent predictions, very low failure rates and transferable knowledge between laboratories. This work also established a new point of view in the evaluation of automated methods not only with segmentation precision, but also with relation to cerebral behavior. The research of [80] presented an ischemic stroke detection system with the help of mathematical models. The approach detected ischemic lesions in MRI employing the Skull Elimination Algorithm (SEA) to remove cranial bone structure and segmentation of the brain region, then the Central Line Sketching Algorithm (CLSA) is applied to bisect the brain image. After that, the Discrete Orthonormal Stockwell Transform (DOST) is performed to extract the attributes and to classify the regions. Finally, the Fuzzy C-Means (FCM) technique is used to clusterize the ischemic stroke region. The system was implemented and tested on a PC with 2.3 GHZ I3 and 4 GB of RAM using MATLAB 7.1 and tested on a database consisting of 20 MRI exams. The proposed system was able to identify and classify the abnormal and normal images and could integrate a CAD system to assist physicians in the detection, segmentation and classification of the regions affected by stroke and reduce the diagnosis time. [81] collected data from 43 cancer patients who developed acute stroke. The determination of the causes and origins of the strokes were grouped according to the

American Society of Clinical Oncology (ASCO).[4] The aim of the study was to explain the distribution patterns of cryptogenic lesions using the voxel-based lesion map technique to examine the differences in clinical manifestations between cryptogenic and conventional effusions in patients with advanced cancer. Clinical data were reviewed and MRI-DWI mapping was performed to visualize the spatial distribution of the lesions. Of the 43 patients, 25 were classified as having cryptogenic etiology and 18 were classified as having a conventional etiology. The mapping of the cryptogenic stroke group showed that lesions accumulate in vascular border zones within the brain, both in the brain and cerebellum, but not in perforating arterial territories. Because conventional non-cancer cerebrovascular ischemic diseases may also occur in cancer patients, it is important to determine whether the ischemic stroke etiology is attributable to the cancer itself or not. Correct diagnoses will lead to more appropriate treatments, not only of the ischemic stroke itself, but also of the underlying malignancy, which will require a thorough knowledge and understanding of the disease.

[82] proposed a computer-assisted methodology for automatic ischemic stroke detection and segmentation in MRI images using the Adaptive Neuro Fuzzy Inference (ANFIS) classifier. The first step consists of a preprocessing, for refinement and noise removal, using the heuristic histogram equalization technique (HHET). Then, the discrete curvelet transformation converts the image into a multiple resolution representation, decomposing the image into directional and low-pass subbands. Then the morphological and texture characteristics that are optimized with a genetic algorithm (GA) are extracted from these coefficients. The selected attributes are used to train the ANFIS classifier that identifies the exams with and without ischemic injury. After classifying the images, the Normalized Graph cut algorithm is used to segment the ischemic stroke region. The method was applied to the ISLES'17 database and simulated in MATLAB R2014b on a machine with 4 GB RAM and 2.4 GHz Core-2-Duo processor. The method reached 97.19% TPR, 98.28% SPC, 96.73% PPV, 95.285% of negative predictive value (NPV), 98.76% ACC and 92.70% of Matthews Correlation Coefficient (MCC). The performance of the proposed methodology was compared with conventional methodologies ([66], [83]–[85]) and obtained superior results in sensitivity, specificity and accuracy. The authors stated that in the future, it would be possible to detect and diagnose strokes using this methodology.

Intravenous thrombolysis is the most appropriate ischemic stroke treatment in a six-hour window. However, to go beyond this window of treatment and for a personalized risk evaluation, it is essential to accurately identify the extent of the penumbra. The work of [86] focused on this goal. They presented a fully automated stroke tissue estimation method using the random forest classifier (FASTER), which automated the estimation of the volume of penumbral tissue in multimodal MRI (DWI, T2w and T1w). FASTER measures the likelihood of tissue damage using a random forest (RF) classifier to map local perfusion characteristics in tissues predicted to be reached, even if reperfusion is established or unsuccessful. The study used anonymized data from the Berne Stroke Registry, a database collected prospectively at the University Hospital of Bern between 2005 and 2013. When applied to 19 test cases with thrombolysis in cerebral infarction (TICI) recanalization after intra-arterial thrombolysis with values between 0 and 2a in the TICI grading system, the mean overestimation of the final lesion volume was 30 ml, compared to 121 ml for manually corrected thresholds. The predicted volume of tissue at risk was positively correlated with the final volume of the lesion ($p \leq 0.05$). The authors concluded that the system may serve as an alternative method to identify tissue at risk and thus may aid in the selection of treatment. However, both training and validation require the inclusion of a multicenter dataset to verify if a generalization of the model is feasible. Another limitation is the source of the data, patients treated with endovascular therapy, outside the six hour window, were selected using non-random treatment criteria, leading to potential bias in response to therapy. Another important work is from [87]. These authors evaluated the feasibility of predicting functional disability of the patient after a stroke using a multi-class SVM and information on the volume and spatial distribution of the injury. The database used in the study consisted of 68 MRI-FLAIR exams of patients 30 days after the stroke occurrence and the level of functional impairment estimated on a modified Rankin Scale (mRS)[5], with the following inclusion criteria: infarct present in the territory of the middle cerebral artery (MCA) and mRS = 0; patient age admission and date of adherence to the National Institutes of Health Stroke Scale (NIHSS). All MRI scans were performed on a 1.5T Sonata or Avanto scanner (both Siemens, Erlangen, Germany). In order to predict the corresponding mRS score, 12 SVM classifiers models were developed, using the lesion overlap values of the different brain region definitions, store laterality information, infarct volume, NIHSS adherence date, and patient age. The best results were achieved with a combination of data from the defined brain regions, including patient age, stroke laterality, NIHSS hospitalization, and systolic volume as additional characteristics in order to overlap quantification. With this configuration the prediction ACC of mRS was 56%, the sliding window precision was 82% and binary precision reached 85%. The authors concluded that predicting the levels of functional impairment associated with lesion volume and location using high-level machine learning techniques seems feasible but needs to be validated using a larger and more representative database. The method described may prove to be especially valuable if combined with the prognostics of the voxel-based tissue results based on multi-parametric images acquired in the acute phase, which allows a real prediction of the patient's future functional outcome.

Table II summarize the comparison among the papers presented in this subsection.

[4]**ASCO**: Founded in 1964, ASCO American Society of Clinical Oncology is the world's leading professional organization for doctors and oncology professionals who care for people with cancer.

[5]**modified Rankin Scale:** Measures the degree of disability or dependence on the daily activities of people who suffered a stroke or other causes of neurological disability.

TABLE II
LIST OF STROKE SEGMENTATION PUBLICATIONS

Study	ST	TE	D	M	Tec	Auto
de Haan et al. [54]	i	CT, MRI (DWI and T2FLAIR)	Pv	DSC, JAC	Clusterize+SPM8	A
Hajimani et al. [56]	stroke	CT	Pv	ACC, PPV, SPC	RBFNN+MOGA	A
Aghaei et al. [59]	h	CT-NC	Pv	Visual and Correlation from Mod Rotterdam and Helsinki sales	Region growing, adaptively adjusted threshold	A
Bhadauria et al. [60]	h	CT	Pv	Visual, comparison between ACC, and, overlap	RG, FCM, active contour-based	A
Sun et al. [61]	h	CT	Pu	TPF, FF	FCM, Otsu's thresholding, SLIC+Graph Cuts	A
Rebouças Filho et al. [62]	h	CT	Pu	Comparison between ACC, and F-Score	LevelSet	A
Yahiaoui & Bessaid [63]	i	CT	Pv	Visual	LP, FCM	A
Maier et al. [64]	i	MRI-DWI, T1, T2, T2FLAIR	Pu	DSC, HD, ASSD	Various techniques	A
Maier et al. [65]	i	MRI-DWI, T1, T2, T2FLAIR	Pu	DSC, HD, ASSD	Various Techniques	A
Karthik & Menaka [66]	i	MRI	Pv	ACC, SPC	Watershed, Curvelet Transform, SVM	A
Griffis et al. [67]	i	MRI-T1	Pv	Comparison between DSC	Naive Bayes + SPM	A
Purushotham et al. [68]	i	MRI	Pv	ROC curve and Regression line	Limiar ADC	A
Chyzhyk et al. [73]	i	MRI-DWI, T1, T2, T2FLAIR, fIRM	Pv		RF+sample AL	A
Maier et al. [69]	i	MRI-DWI, T1, T2, T2FLAIR, fIRM	Pv	DSC, ASSD, HD, precision and recall	ET	A
Forkert et al. [87]	i	MRI-DWI	Pv	ACC, TPR, sliding W and B	SVM	A
Subudhi et al. [74]	i	MRI-DWI	Pv	Pixels quantity	FCM	A
Nag et al. [75]	i	MRI-DWI	Pv	DSC, JAC, CR, Regression line	GMM	A
Zhang et al. [76]	i	MRI-DWI	Pu and Pv	DSC, TPR, F-Score	3D FC-DenseNet	A
Pustina et al. [79]	i	MRI	Pv	Comparison between LSM	LINDA	A
Jayaram & Menaka [80]	i	MRI	Pv	Mean, median and SD	SEA + CLSA + FCM + DOST	A
Sivakumar & Ganeshkuma [82]	i	MRI	Pv	PPV. NPV	Classifier ANFIS + HHET equalizer and GA	A
Achiha et al. [81]	i	MRI	Pv	Statistical Analysis	Voxel-Based Lesion Mapping	A
McKinley et al. [86]	i	MRI-DWI T1, T2	Pv	Comparison between lesion volume	FASTER	A
Chen et al. [77]	i	MRI-DWI	Pv	DSC	EDD Net e a MUSCLE	A

The **ST** column indicates the stroke type, (i) ischemic and (h) hemorrhagic. **TE** indicates the type of exam. **D** indicates if the database is public (Pu) or private (Pv). **M** indicates the evaluation metrics. **Tec** indicates the technology used. And **Auto** indicates the automation level, (A) automatic, (S) semi-automatic or (M) manual.

C. Stroke Classification

Disease identification based on the processing and analysis of medical images if of great importance to assist doctors in the decision making process. The most important works about types and subtypes of stroke classification are perhaps the articles [88] and [89]. They developed a new method to extract characteristics based on human tissue density patterns to integrate a system of classification of lung disease and stroke type in CT images, called Human Tissue Density Analysis (AHTD). The AHTD analyzes the radiological densities of human tissues for the extraction of suitable characteristics in lung and brain CT scans. The system was tested on a chest and cerebral CT database obtained in partnership with the Walter Cantidio University Hospital and the General Hospital of Fortaleza (HGF), Fortaleza, Brazil. The results were compared with the GLCM extractors, Hu moments, statistical moments, Zernike moments, Fourier elliptic characteristics and Tamura characteristics. Validation was carried out with the Bayes, k-NN (k = 3 and 5), optimum path forest (OPF) (Euclidean and Guassian), multilayer perceptron (MLP) with 20 hidden layers and SVM (linear and RBF kernels) classifiers with each feature extractor in the two databases. The attributes were extracted from the cerebral images in 3.8 ms and obtained an ACC of 98.81% for the stroke type detection and classification. For a complete analysis of the results, the Friedman statistical test was applied on the accuracy and F-Score results of each classifier and extractor combination. The AHTD achieved its best result among all extractor/classifier combinations with the Euclidean distance and OPF classifier, reaching an average ACC of 99.30%. These results show that the proposed method can be used to classify diseases into medical images, and can be used in real-time applications due to its fast extraction time of suitable attributes.

[90] used texture characteristics, instead of intensity-based characteristics, to classify the stroke type in brain CT images. The system consists of a pre-processing that removes the bones of the skull and extracts texture characteristics of the region. The next steps are to delineate the area affected by the stroke and

analyze the characteristics using the SVM classifier. The classifier was implemented with three kernel functions (linear, quadratic and RBF) in order to investigate the appropriate choice for the stroke detection and classification. The authors used their own database to validate the proposed method, which is not publicly available, but consists of CT scans of patients of various age groups. The method achieved ACC results of over 80% with the three kernels used. The most promising results were from the linear kernel with 92% TPR, 89% SPC and 91% ACC. The evaluation of the proposed approach validates its effectiveness and robustness; however this approach should be evaluated on larger databases. The use of large and varied sets of CT scans should improve system performance and ensure repeatability of the performance. [91] developed a solution based on texture analysis for stroke tissue recognition on CT scans. The proposed method has two steps: segmentation of regions of interest and stroke region classification through the extraction of different attributes. The proposed solution used several numerical descriptors in the Fourier 2D, Fourier 2D polar and multiscale (i.e., wavelet, complex wavelet and contourlet domain) domains. The results showed the effectiveness of the stroke segmentation. The authors did not describe and do not make available the database used. The results of the experiments were close to 75%, the cases used were previously evaluated by radiologists with a mean ACC of 61.0% (range of 47 to 84%), TPR of 56% (range of 40 to 81%) with SPC of 92% (ranging from 66 to 100%) and 97% ACC (range of 91 to 100%). Comparing the results of the patch-based analysis and radiologists, the diagnosis is not simple, but the method developed expands the set of useful resources and classifiers known for stroke detection and differentiation in CT.

Detection, correct localization and identification of the hemorrhage stroke are essential for the diagnosis and determination of the treatment. Several methods of hemorrhagic stroke detection and localization are being developed. However the characterization and classification of the type of hemorrhage is still in its early stages. [92] proposed an algorithm for hemorrhagic stroke detection and classification in brain CT images. First, a pre-processing is performed to remove parts that can reduce segmentation performance. In the segmentation stage a modified version of the Distance Regularized Level Set Evolution (DRLSE) algorithm was configured according to the application, in this way, the smallest or more uncertain hemorrhages can be detected. To improve the classification performance, an optimal resource selection algorithm was used combining the Genetic Algorithm (GA) and Adaboost algorithm. The proposed method was submitted to a database with 627 images divided into 5 classes (Epidural Hemorrhage (EDH), Subdural Hemorrhage (SDH), Intracerebral Hemorrhage (ICH), Intraventricular Hemorrhage (IVH) and Normal). To evaluate the attributes of the selection algorithm and the SVM classifier, a comparative analysis was performed with the MLP, KNN and SVM classifiers before and after using the GA/Adaboost resource selection algorithm. In the first level, class IVH was separated from the normal class with an ACC rate of 92.46% and in the second level, three classes SDH, EDH and ICH were classified by the multi-class SVM classifier with a ACC rate of 94.13%. The time spent processing each image was 15.57 seconds, which can be reduced by at least 20 to 30 times in a C++ implementation.

The precise location and stroke extension is important in determining the severity of the brain injury. However, it is difficult to develop an accurate algorithm for detecting stroke lesions due to size variation, morphological structure, and similarity of lesions with the normal parenchyma. [93] designed an automatic system based on the optimization of clustering for the fast and accurate ischemic stroke segmentation and classification according to the Oxford categories: partial anterior circulation syndrome (PACS), lacunar syndrome (LACS) and total anterior circulation stroke (TACS). The algorithm, named DT-FODPSO, integrates the advantages of Delaunay triangulation (DT) and Fractional Order Darwinian Particle Swarm Optimization (FODPSO). The tests were performed on a database composed of 192 MRI slices acquired with a Signa HDxT 1.5T Optima Edition machine (GE Healthcare, Waukesha, WI) from the Institute of Medical Science and SUM Hospital, Bhubaneswar, Odisha, India. The images were preprocessed with the Wiener filter for noise re-examination and then the DT method was applied to delineate the lesion based on its intensity distribution. The GLCM extractor is then used and the extracted features are applied to the SVM and Random Forest (RF) classifiers to identify the ischemic stroke subtype. The classifiers were used on the Weka platform with a 10-fold leave-one-out and cross-validation approach. The FODPSO mean ACC was 0.92 while the DT-FODPSO obtained 0.94, using the SVM classifier. Using the RF classifier, the mean ACC was 0.93 and 0.95 using the FODPSO and DT-FODPSO, respectively. The values of all other measured parameters were better with the DT-FODPSO method along with the RF classifier. This combination achieved an average TPR of 0.94, JAC of 0.88 and DSC of 0.94. The proposed method was compared to other 7 methods that used Fuzzy Clustering, RF, Naive Bayes and CNN, obtaining a DSC 14% better than the second best method. The DT-FODPSO method was superior in terms of the evaluated parameters and was able to detect multiple lesions. Therefore, the proposed method is able to detect lesion patterns more efficiently in cerebral MRI compared to the other techniques reported. The main limitation of the study is to calculate the volume of the lesion, which could be estimated from segmented lesions in a series of slices of the same exams. [94] developed a method to identify the best MRI enhancement techniques to classify intracerebral hemorrhage (ICH). This study considered five MRI examinations of patients diagnosed with hemorrhagic stroke by the neurology unit of Pusat Perubatan Universiti Kebangsaan of Malaysia (PPUKM). The images were acquired in DICOM format and were processed with contrast enhancement, histogram equalization, image sharpening and median filter techniques in MATLAB software. All images were compared based on their Absolute Mean Brightness Error (AMBE) and entropy values. The general results show that the median filter was the best image enhancement technique with AMBE mean values and entropy of 0.0885 and 5.14772, respectively. The second best method was the image sharpening and power law intensity transform with gamma correction. Histogram equalization is not suitable for improving MRI, since it corrupts the images by greatly increasing their brightness. The deficiency of the study was the use of a very restricted database and it excluded any patients with secondary ICH, which prevents the generalization of the results.

Electromagnetic Tomography (EMT) is an imaging technology that has been attracting interest for being non-invasive, safe, besides having high usability, low cost and silent, and EMT technology is appropriate for claustrophobic patients. [95] and [96] developed studies to demonstrate that the stroke detection and classification with EMT technology is possible. The authors compared the results of image reconstruction using the EMT sensor brain scanner (BRIM G2) with the results obtained by a computational model to demonstrate that the technology has the ability to detect and differentiate the stroke type. Experiments in human head phantom models showed that the inhomogeneities with relatively poor contrast ($\approx -10\%$) can be detected, proving that the EMT may be applied to the detection, classification and monitoring of strokes. Despite its more complicated structure, the overall contrast differences expected for a human head are smaller than the human head phantom employed. However, there is also a clear need to improve the overall image quality, which is related to a hardware and software improvement of the current configuration. Another disadvantage is the relatively weak spatial resolution, which is related to the frequency spectrum employed. In particular, for brain imaging applications, the usual frequency range of 0.5 to 2.0 GHz is restricted due to the high attenuation of brain tissue. In the work of [97], the authors investigated the viability of EMT in the continuous monitoring of stroke, however, the detection and identification represented a great challenge, since the acquisition of images in an iterative form requires the solution of an inverse problem, which requires a large computational capacity. The objective of the research was to solve the inverse problem associated with a prototype developed by EMTensor GmbH (Vienna, Austria) using state-of-the-art modeling and large amount of parallel high-performance computing. To test the viability, synthetic data corresponding to a numerical model of a human head with a stroke that increases over time from a small hemorrhagic stroke to a large hemorrhage were used. In this case, the relative complex permittivity is assumed to be nonhomogeneous. As the system will be used to detect ischemic strokes or hemorrhagic strokes and to monitor the treatment, the execution time of reconstructions must be fast. Therefore, they used high order finite element methods, parallel pre conductors with the Domain Decomposition and Domain Specific Language method with the open source FreeFEM ++ solver. The reconstructed images for each test case were obtained with a total computation time of less than 2 minutes (94 seconds for the large path case) using 4096 Cuda cores. The authors conclude that EMT is an imaging modality that can compose a CAD system and be an effective complement to CT and MRI technologies. And because it is a non-invasive, transportable/portable device, it would have clear clinical applications at the bedside in a neurological intensive care unit (NICU).

The synthesis of the comparison among the articles of sub-Section III-C is summarized in the Table III.

IV. Dataset Description

Among all the studies listed in this review, 88% did not provide databases during training or validation tests. Most of the works only listed the technical information of the equipment used for image acquisition. Few papers emphasized information on voxel windowing, final resolution, number of slices, cut thickness or quantification. In some studies, this information was omitted, specifying only the location where the exams were taken or the hyperparameters optimization and adjustment techniques. Only one study specified the qualification and identification of the specialist who made the diagnosis or made the ground truth markings. In this section, we present a description of the properties of the databases used by the aforementioned articles, made publicly available by the authors, as well as the methods and configurations used in acquisition.

A. CT Lesion Stroke Dataset

This database was made available by [36], consisting of 25 brain CT scans of ischemic stroke, hemorrhagic strokes and normal patients. Images and diagnosis were obtained with the support of Trajano Almeida Clinic - Diagnostic Imaging in Fortaleza, Ceará, Brazil. For ethical reasons, they omitted the identification of the patients.

The tomographic model used to acquire the images was the HiSpeed CT/and Dual1 from General Electric. In the image acquisition process, the tomographic sections were performed at the base of the axial plane, under the following conditions: cut thickness 0.7 mm, field of view 230 mm, electric voltage in the tube 120 Kv, electric current in the tube 80 mA, dimensions 512 $\times$ 512 pixels and voxel window size of $0.585 \times 0.585 \times 1.5$ mm with a quantification of 16 bits, window of 40 HU and window amplitude equal to 80 HU. The database presented non-regular patterns, irregular lighting and different structural characteristics. Some slices presented poor quality, which could negatively influence the results, so they were discarded, resulting in 300 images, of which 100 were healthy brain images, 100 with ischemic stroke and 100 with hemorrhagic stroke.

The images were in the DICOM format, which is the standard supported by most medical diagnostic devices. After the reading, the images were submitted to a conversion of 16 bits to 8 bits in each pixel, aiming to facilitate and accelerate the manipulation of the images without loss of relevant data. The authors provided the database in the original format, already pre-processed, with the segmented stroke region and the radiological density maps. Fig. 4 shows some examples of the images that are publicly available and can be obtained at http://lapisco.ifce.edu.br.

[89] used the images for the AHTD algorithm validation in the extraction of characteristics based on the radiological densities of human tissues. In [88] the database was used in the validation of the AHTD extractor, which is algorithm specialized in brain tissues. [62] used 100 images of hemorrhagic strokes to verify the efficiency of the LSBRD method in the segmentation of hemorrhagic regions.

TABLE III
LIST OF PUBLICATIONS FOR TYPE AND SUB-TYPE STROKE CLASSIFICATIONS

Study	ST	TE	D	M	Tec	M
Rebouças Filho et. al. [88], Rebouças Filho et. al. [89]	stroke	CT	Pu	ACC, SPC,TPR, PPV, F-Scopre, time, Friedman's test	AHTD+Bayes, OPF, MLP, SVM	A
Jeena & Kumar [90]	stroke	CT	Pv	ACC, SPC, TRP	SVM (Linear, Quadratic and RBF)	A
Ostrek et. al. [91]	stroke	CT	Pv	ACC, SPC, TPR, p	LogitBoost+Wavalet	A
Shahangian & Pourghasse [92]	h	CT	Pv	ACC, TPR, SPC, PPV, NPV, error	GA+Adboost, k-NN, MLP, SVM	A
Subudhi et. al. [93]	i	MRI	Pv	DSC, JAC, ACC	Winner Filter, GLCM, DT-FODPSO	A
Chellappan et al. [94]	h	MRI	Pv	AMBE, Entropy	Power law, HE, Sharpening, Median Filter	A
Hopfer et. al. [95], Semenov et. al. [96]	stroke	EMT	-	Visual analysis	EMTensor brain scanner	A
Tournier et. al. [97]	stroke	EMT	-	Visual analysis	High-order finite elements, parallel preconditioners with the Domain Decomposition method	A

The **ST** column indicates the stroke type, (i) ischemic and (h) hemorrhagic. **TE** indicates the type of exam. **D** indicates if the database is public (Pu) or private (Pv). **M** indicates the evaluation metrics. **Tec** indicates the technology used. And **Auto** indicates the automation level, (A) automatic, (S) semi-automatic or (M) manual.

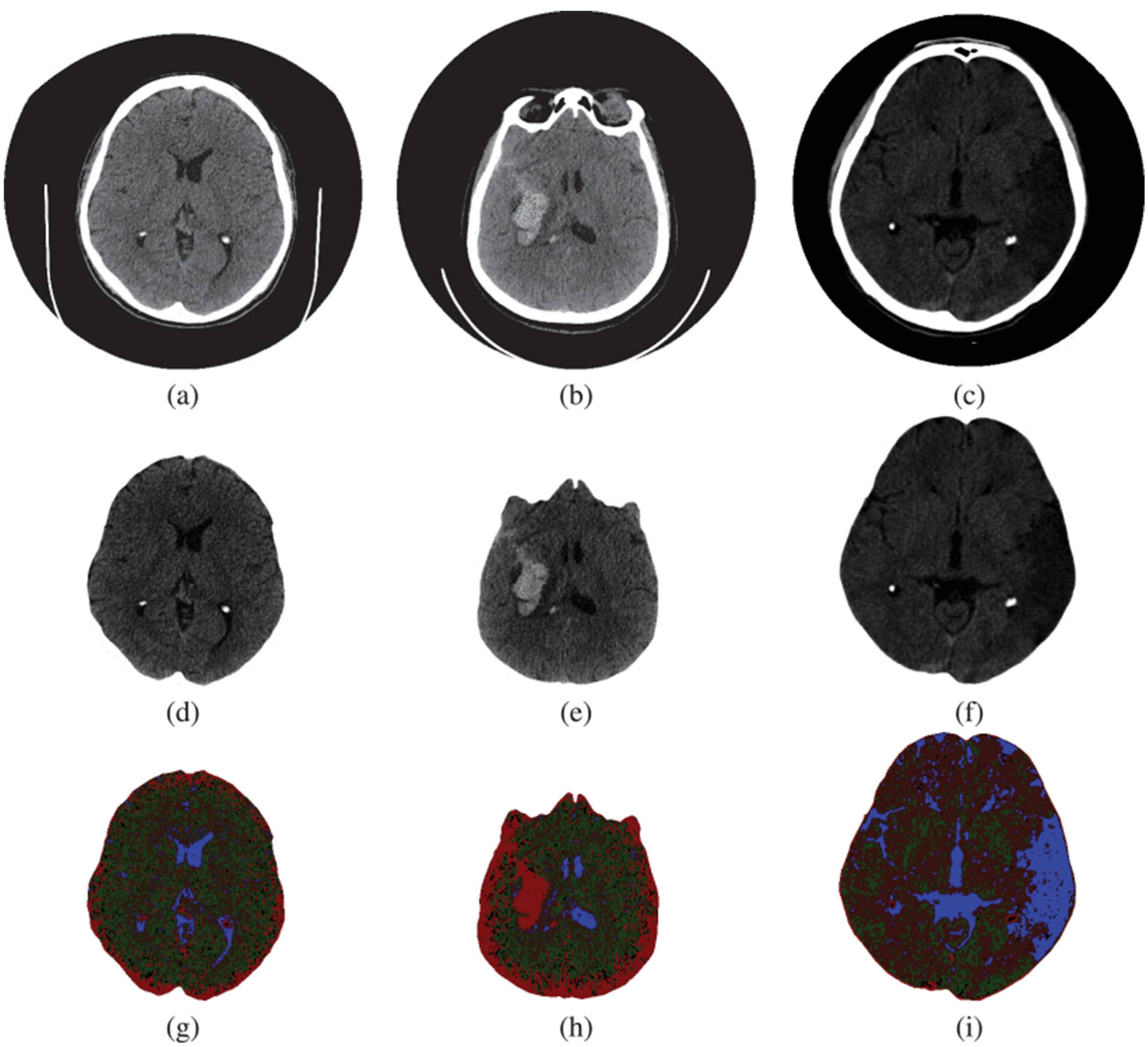


Fig. 4. Some images used in the experiments: (a, b, c) Cranium CT original images; (d, e, f) brain segmentation; (g, h, i) radiological density map. Source: [36].

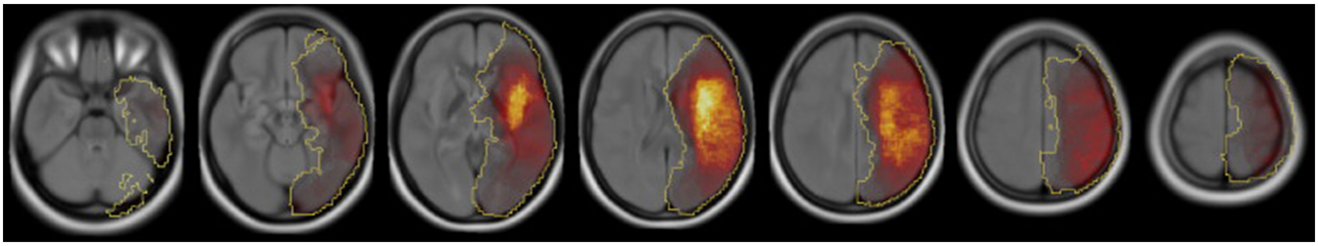


Fig. 5. Examples of images that compose the MRI Lesion Stroke dataset. Source: [65].

B. MRI Lesion Stroke Dataset

The database used in the research in [65] and [69] consisted of 37 cases that had been acquired for the studies of [70]–[72]. All cases were acquired on a 3T Achieva 3.0T TX scanner (Phillips, Amsterdam, Netherlands). Of the 37 patients, 17 were women. The average age was 65.5 ± 15 years old. The available sequences were T1w, T2w, FLAIR and DW. In addition, an apparent diffusion coefficient (ADC) map was calculated from the DW images. A detailed list of image resolutions is available at sciencedirect.com/science/article/pii/S0165027014004038. All images used in this study can be found through Figshare (http://dx.doi.org/10.6084/m9.figshare.1585018). The pre-processing cases, the ground truth and segmentation images are available at (www.isles-challenge.org). Some of the cases have recently been incorporated into the ISLES 2015 challenge dataset, along with a larger set of images. Fig. 5 shows some of the images that composes the dataset.

C. Ischemic Stroke Lesion Segmentation (ISLES) Dataset

[64] and [76] used the challenge database Ischemic Stroke Lesion Segmentation (ISLES) organized in conjunction with the $18th$ International Conference on Medical Image Computing and Computer Assisted Intervention (MICCAI 2015). ISLES provided a platform for a fair and direct comparison of methods for the segmentation of multi-spectral ischemic MRI lesions. The ISLES platform provided databases for two challenges: sub-acute ischemic stroke lesion segmentation (SISS) and acute stroke penumbra (SPES).

The SISS database includes 64 MRI-T1 scans TFE/TSE, T2 TSE, DWI, and FLAIR cases of subacute ischemic stroke provided by the Schleswig-Holstein University Medical Center in Lubeck, Germany, and the Department of Neuroradiology at the Klinikum rechts der Isar in Munich, Germany, both centers are equipped with 3.0T Phillips systems. The SPES database is composed of patient exams, with a minimum age of 18 years old, treated at the University Hospital of Bern between 2005 and 2013. Patients included in this data set were diagnosed as having a stroke due to MRI-DWI and PWI documented in angiography by digital subtraction. MRIs were generated in a 1.5 T system (Siemens Magnetom Avanto) or 3T MRI (Siemens Magnetom Trio) and were composed of T1c, T2 and DWI sequences. Following the stroke protocol, the MRI-DWI has a total of 24 slices with 5mm thickness, repetition time of 3200 ms, echo time of 87 ms and resolution of 256 $\times$ 256. The MRI-PWI used the standard dynamic sensitivity contrast for MRI enhancement, and were acquired with 1410 ms repetition time, 30 ms echo time, 230 $\times$ 230 mm field of view, voxel size: 1.8 $\times$ 1.8 $\times$ 5.0 mm, slice thickness 5 mm, 19 slices and 80 acquisitions. Figs. 6 and 7 show examples of the databases of the SISS and SPES challenges respectively.

All examinations were completely anonymized by removing all patient information from the files and the facial bone structures of the images, which were released and approved by the local ethics committee: Release under number Az.14-256A. ISLES is currently in its 4th edition, and its databases remain publicly available through an online assessment system to serve as a benchmarking resource.

Table IV summarizes the most important information in these databases:

Although all approaches make an effort to quantify the accuracy of the results, most do not provide the database used, which is a critical issue. The lack of publicly available medical datasets, with their ground truths, makes it difficult to develop and compare studies on stroke detection, segmentation and classification in medical images. Besides, it makes it hard to compare the various works listed in this review. A very recent work [65] compares a number of classification algorithms in a common data set, but these do not fully represent the state of the art and are not implemented by their respective authors.

V. Discussion

This section presents an analysis and discussion of the papers presenting the limitations, open questions and some opportunities for future research. The related works were grouped according to the main purpose and organized by the medical image type.

A. Stroke Detection

Among the works that use CT images, the main problems detected are linked to small databases that limit the generalization of the results and the dependence of the reading by a specialist to confirm the infarcted insula area ([15], [34]). Most detection works treat the ischemic and hemorrhagic stroke types separately. [36] developed a detection system using a CNN trying to overcome this situation. However, even with results close to 99% of ACC, the authors affirm that it is necessary to increase the database and to test different deep learning methodologies. [35] shows that even using first-line diagnostic methods, such as CT-NC, early detection of ischemic strokes remains a challenge

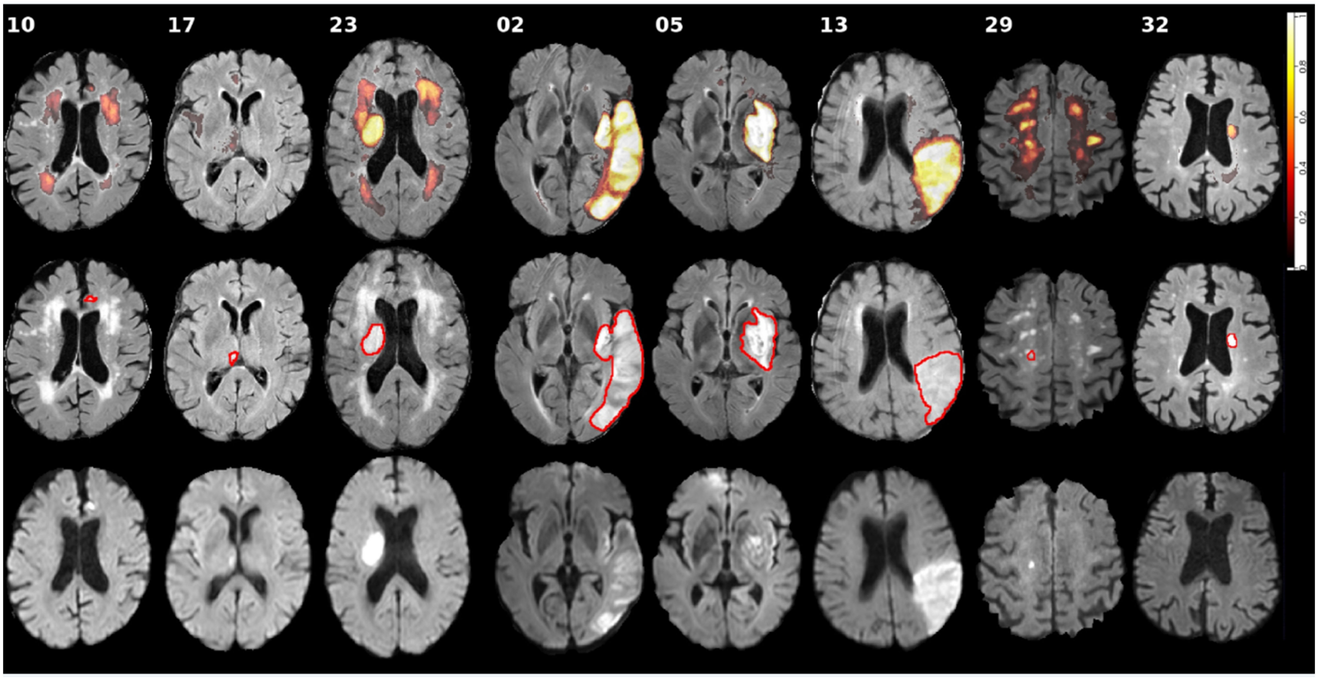


Fig. 6. Different visual results for selected difficult (10, 17, 23), easy (2, 5, 13), and second center (29, 32) cases from the SISS testing dataset. Source: [64].

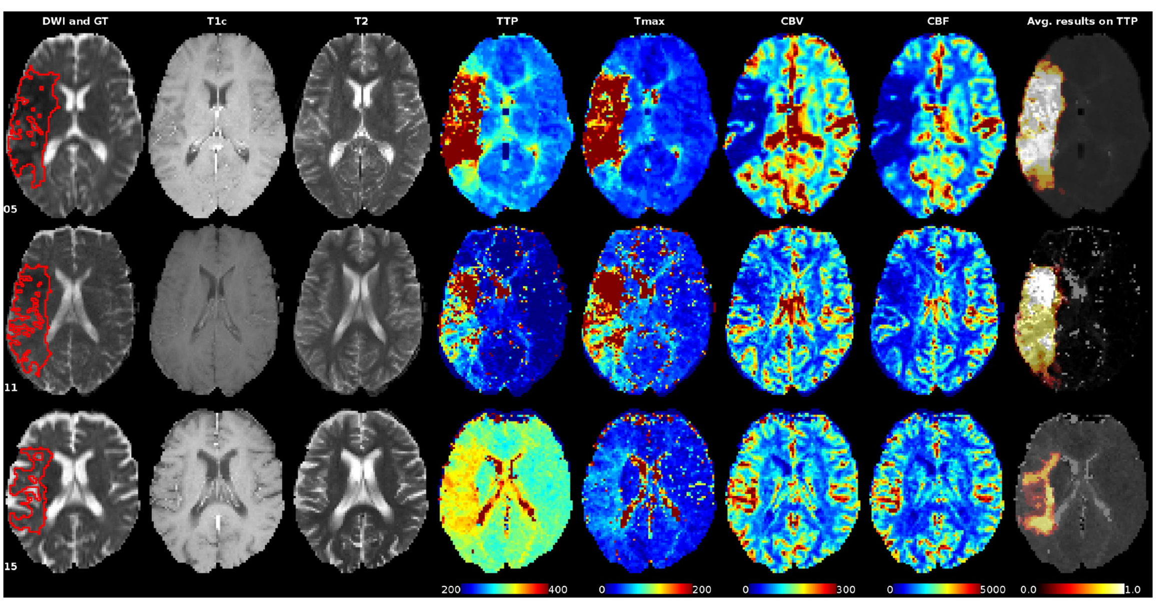


Fig. 7. Sequences examples of cases with a low (05 and 11) and high (15) average DC score over all 7 teams participating in SPES. Source: [64].

TABLE IV
MAIN PUBLIC DATASETS USED BY THE PAPERS CITED IN THIS WORK

Dataset	Type	Composition	Equipment	Format	Dimensions	Window size
Stroke Lesion	CT	25 exams	HiSpeed CT/e Dual1 GE	DICOM	512x512 p	0,585x0,585x1,5 mm
Stroke Lesion	IRM	37 images	3T Achieva 3.0T TX scanner	NIfTI	Not Specified	Not Specified
ISLES - SISS	FLAIR, T2w TSE, T1w TFE/TSE, DWI	64 images	Philips - Ingenia 3.0T System MR	NIfTI	Not Specified	Not Specified
ISLES - SPES	T1c, T2, DWI, CBF, CBV, TTP, Tmax	50 images	Siemens Magnetom Avanto 1,5 T and Trio 3T MRI	NIfTI	256x256 p	1,8x1,8x5,0 mm

for the human reader. This clearly shows the difficulties involved for the manual or automatic detection and segmentation based only on the analysis of the HU level and histogram techniques. Moreover, this field of research is quite challenging and is open to new techniques. The only work that used MRI images was [37] who evaluated the performance of the k-NN and MMD classifiers in the stroke identification process with intense tests using the LabView software and three different distance metrics. However, the work was restrict to a database of 50 images, which was not made available and the information about the acquisition equipment was omitted. This prevents a replication of the results or a comparative test in a similar environment.

An innovation found was the use of blood analysis to expedite the ischemic stroke diagnosis [42]. These authors used GA/K-NN to optimize the identification of a gene expression pattern. The transcriptional pattern identified in this study showed a strong diagnostic potential, however, even with 98.4% accuracy in identifying the results there is a need for further evaluation to determine its true clinical efficacy. Another work that did not use one of the common techniques is from [43]. They used EEG and EOG tests to detect ischemic strokes based on the premise that a person with ischemic accident has a reduction in cerebral blood flow and this tends to slow down the EEG signal. The results show that this method has a great potential and could be used to identify a person with an ischemic accident.

The use of MWI to estimate the dielectric characteristics of cerebral parenchyma has attracted the attention of various researchers ([46]–[48], [51]–[53]). MWI can integrate a rapid and accurate detection and localization system in symptomatic patients. The use of non-ionizing radiation, unlike CT, and with the low set up cost makes this technique feasible for use in clinical medicine. In [45] an ultra-wideband antenna was developed to detect stroke. The system is based on the premise that there is an obvious difference in the dielectric constant between the stroke affected area and the normal area. The system, combined with the Confocal algorithm, achieved results that indicate viability, however the system still requires performance tests in more accurate models and in real patients. In [44] the authors developed a system composed of a set of 36 antennas equally distributed in a circumference to be placed around the head generating microwave images for hemorrhagic stroke detection. The results are encouraging and present the possibility of developing small, low-cost diagnostic devices that can be transported in ambulances and medical vehicles. [50] proposed a methodology based on learning-by-examples for real-time detection of a stroke from microwave dispersion measurements. The results achieved perfect discrimination, ACC of 100% and 0% error. However, the study lacks experiments on real people with various types of stroke.

B. Stroke Segmentation

We identified 25 relevant articles related to segmentation. After an analysis we extracted some evidence on this topic. Most studies (68%) used MRI scans with different weighting levels (DWI, T1, T2 and FLAIR), the others were based on CT scans. Only the article [54] used both types of neuroimaging to test the efficiency of the Clusterize algorithm in the semi-automatic segmentation process. The results showed that the similarity between the injury maps was excellent, suggesting that the accuracy was comparable to the ground truth. The differential of this semi-automatic approach lies in the fact that it allows a routine of human quality control not implemented in fully automated methods, avoiding the perpetuation of errors in later analyses.

The success of image analysis and classification systems depends heavily on the quality of the segmentation processes. The selected works demonstrated the efficiency of the different DIP techniques used in the segmentation. Among them we can mention the Threshold methods ([59], [61], [68]), Region Growing methods ([59], [60]), Watershed method ([66]), Fuzzy Logic based algorithms (([60], [61], [63], [74], [80]), Statistical Analysis methods ([79], [81]), Active Contours techniques ([60]) and Level Set methods ([62]). Another work used ML techniques such as GMM ([75]) and LogitBoost ([91]) and classifiers such as the Naive-Bayes ([67]), Random Forest ([69], [73], [86]), SVM ([38], [87]) and Adaptative Neuro Fuzzy Inference ([82]), as well as Deep Learning ([76], [77]).

Only [56], [91] performed the segmentation process independently of the type of stroke, all others were focused on only one type. The only works that made the databases publicly available were [62], [64], [65], [76], and they also described the examination methods and the characteristics of the equipment used in the acquisition. In all the studies, the validation of the results was carried out by comparative analysis with the gold standard through quality metrics of diagnostic tests: reproducibility, ACC, TPR, SPC, PPV, F-Score, DSC, JAC, ROC curve and other aspects related to the design and analysis of these studies.

C. Stroke Classification

Among all the articles that met the inclusion requirements, i.e., perform detection and classification, only 8.73% were aimed at identifying and classifying strokes types or subtypes. Among these, 4 used the CT scans ([88]–[90], [92]), 2 MRI scans ([93], [94]) and 3 used EMT exams ([95]–[97]).

The works [88], [89] presented a new feature extractor that can be configured to work on brain and lung images. An extensive comparative analysis was performed between several feature extractors and four classifiers with several configurations in order to find the extractor/classifier configuration with the best classification result. It is worth mentioning that these works were the only ones works that made the database publicly available. The work of [90] used texture features and an SVM to classify the stroke type in CT scans. The results of the proposed approach proved its effectiveness and robustness, however this approach must be extended to include larger databases. The use of varied sets of CT scans should improve system performance and ensure repeatability of the resulting performance. Unlike the other works that used CT, the article [92] proposed a system for the detection, segmentation and classification of hemorrhagic strokes in 4 sub-types. The tests were performed on a database consisting of 627 images; however the database was not made available. The system used a multiclass SVM and achieved an

ACC rate of over 92% for class IVH and 94.13% for SDH, EDH and ICH classes. The processing time for each image was 15.57 seconds, but the authors claim that this time can be reduced 20 to 30 times with a C++ implementation.

Among the papers that used MRI exams the article [93] presented the DT-FODPSO algorithm that integrated an automatic system for hemorrhagic stroke segmentation and classification according to the Oxford categories (PACS, LACS, and TACS). The algorithm was tested on a database composed of 192 slices of several MRI exams. Compared with other classifiers, it obtained a DSC 14% better than the others and was able to detect multiple lesions. The results confirmed the efficiency of the algorithm, however it used a private database with a small number of samples and without explaining the selection criteria of each slice compromises the generalization of the results. In addition, there is a limitation in calculating the lesion volume, which could be estimated from segmented lesions in a series of slices of the same exams. Article [94] presented a study that analyzed the techniques of contrast enhancement, histogram equalization, image sharpening and median filter for the improvement of MRI and for the hemorrhagic stroke classification in Intracerebral hemorrhage (ICH) and cerebral amyloid angiopathy (CAA). Although the study identified and listed the best techniques, the methodology and the small number of tests used in the tests reduces the scope of the results.

In the articles [95], [96] the authors demonstrated, through tests and simulations, that EMT technology can compose a CAD system and can be an effective complement to CT and MRI. However, while the benefits and results proved that it can be applied to detect, segment, classify and stroke monitor strokes, there is also a clear need to improve the overall image quality. This is related to an improvement in the current hardware and software available. Another disadvantage was the relatively weak spatial resolution, which is related to the frequency spectrum employed. In particular, for brain imaging applications, this frequency spectrum is restricted due to the high attenuation of brain tissues. Article [97] investigates the feasibility of the microwave imaging technique for continuous stroke detection and monitoring. In order to test the viability, synthetic data corresponding to a numerical model of a human head with a stroke that increases over time from a small hemorrhagic stroke to a large hemorrhage was used. The reconstructed images for each test case were obtained with a total computation time of less than 2 minutes (94 seconds for the large path case). However, detecting and identifying the stroke type using EMT represents a major challenge. This is due to its iteratively image acquisition, that requires a solution of an inverse problem, which demands a high computational capacity, efficient numerical modeling and high parallel computing performance.

D. IoT and Online Monitoring of Neuroimages

Much research has been carried out using the search query "IoT" as a keyword. Only one work, published in 2019 is inside the scope of this review and addresses IoT for the classification of strokes. Although the article is outside the time limits of this review, its scientific importance is worth the citation. [98] developed an IoT framework for the classification of strokes from CT images. An image is sent to the system which then uses the concept of transfer learning to perform a feature extraction through the main CNNs in use today such as AlexNet, VGG, Inception, ResNet, MobileNet, and others. After extracting the features, a series of machine learning techniques for classification are applied such as Random Forest, kNN, SVM, MLP and Bayesian classifier. After this process the results are presented through the online framework, the results presented by the authors are very positive, obtaining values greater than 99% of accuracy with some combinations of CNN and classifiers. This shows how IoT systems can be of extreme relevance for the treatment of strokes and can facilitate the diagnosis of these traumas in remote locations or locations that do not have specialists available, since the whole process requires only a smartphone or computer and internet access. After this the doctor, even being elsewhere, can diagnose the patient with the aid of this tool.

In relation to the online processing and monitoring of neuroimages, the papers of [95]–[97] highlighted that the EMT technology presents promising results, and indicated the possibility of developing a tool for *in loco* monitoring of the patient with stroke. However, the great challenge is in the process of image acquisition, which demands high computational capability, efficient numerical modeling and high parallel computational performance.

Other important works do not focus only on the online monitoring of the post-stroke patient in order to assist the specialist and the patient in the process of post stroke recuperation. These works used gadgets like: personal digital assistant (PDA), smartphones smartwatches, smartbands, and tablets, among others. The extracted information from these sensors can be extended to different purposes, such as extraction, monitoring of information, monitoring the prognosis of neuronal diseases and in neurorehabilitation.

Neurorehabilitation services are essential in post-stroke treatment. [99] attempted to determine the feasibility, efficacy, acceptability, and barriers in using iPads as a tool to aid in the post-stroke neurorehabilitation process. They concluded that the incorporation of tablets has potential because they help to maintain the interest of the patients improving the clinical results and reducing the abandonment of the tasks. However, few preliminary studies have shown positive results for home rehabilitation using tablets. Therefore, further research is needed to provide sufficient data to prove the effectiveness of tablet rehabilitation. [100] developed a portable functional prototype of a Brain Computer Interface (BCI) capable of tracking brain tumors and helping to determine the type of stroke, allowing early intervention. Other uses include cerebral and vascular activity mapping and provide a new non-invasive method to measure blood pressure. However, the validation process for these applications requires continuous research that will involve considerable future effort. [101] developed a framework for online detection of movement-related cortical potential (MRCP) signals associated to movements with different kinetic profiles. The main focus of this work is to implement the detection and classification of MRCP signals in a portable device and also demonstrate the ability to decode, in real time, cerebral signals to be used in rehabilitation clinics. The results are promising, making the system a viable option to be adapted for the rehabilitation of a patient with stroke.

[102] developed an intelligent and low cost system for the diagnostics of the writing efficiency and handshake of post-stroke patients. The device consists in a sensory glove VMG30 for feature extraction and a Bayesian network, which transform the extracted data into probabilistic estimations. The novelty of the system is in the way that it joins the sensorial information and interprets it as probabilities of impairment in the control of hand movements. The final result can be made available to a specialist remotely. This may address the needs of underprivileged people due to many circumstances such as the lack of effective communication between the patient and the specialist, the unavailability of adequate medical facilities and financial constraints that prevent low-income people from obtaining the necessary treatment. [103] carried out research into human activity recognition (HAR), which is a fundamental component for stroke diagnosis. The authors produced a new wearable device, easy to use and with low cost, for movement detection. The proposed device can distinguish normal rest from a paralysis caused by a stroke. Despite the promising results, the authors emphasized that the current experiments should be considered preliminary, since no exhaustive test with a high-risk population was performed, but the results are remarkable and have encouraged them to continue with this line of research.

E. Challenges and Future Trends

Among all the reviews, a series of challenges which each method seeks to overcome were highlighted. The issues that were addressed the most were the need to optimize computational techniques, the extraction and selection of more suitable hyperparameters and the limitations of hardware performance. The greatest difficulty, present in most researches, is the lack of a database of reference exams, i.e., a complete database composed of several types of neuroimaging, in several phases of the disease, with their clinical reports and the regions of interest (ROI) segmented by a specialist. This lack of a reference database causes a major impasse for the development of new research and for a comparative analysis of existing computational methods and techniques. Throughout this review we found only three complete databases that were made available by the authors. Two databases are composed only by one type of examination: MRI or CT. The other database that has become popular since 2015 is the ISLES, an international challenge for the segmentation of ischemic stroke. Despite the availability of a database with several types of neuroimaging, allowing several researches to test and compare their methods and results, this challenge is restricted only to ischemic stroke.

Even though the evolution in neuroimaging research, there is still a large deficit to be overcome which is the absence of quality annotated medical data. Several papers use their own database and only expose the configurations of the equipment used to acquire the exams. However, only the settings of the tomograph are not sufficient to replicate the exams. This generates great difficulty in reproducing the results of the analyzed works. In addition, in some cases, when the authors provide the bases, the examinations are not accompanied by the reports or markings of the ROIs required for a quality analysis.

The major difficulties in creating a database with quality annotated data are the time required to compile all exams and make the annotations, ethical issues to preserve patient identity, and often lack of collaboration between specialists and the academic community. This could be solved with efforts between medical specialists and researchers in order to provide new databases of quality annotated data. These efforts could improve methods for data analysis and generate new CAD systems, increasing the applicability of the techniques used in neuroimaging. Such evolution in neuroimaging processing and analysis techniques will significantly contribute to expand the understanding of the interactive processes of organs and systems, thus providing a better diagnosis and a more efficient treatment.

Another important challenge to overcome is the lack of studies aimed at identifying and classifying stroke in its subtypes: intracerebral hemorrhage, subarachnoid hemorrhage, and brain ischemia due to thrombosis, embolism, or systemic hypoperfusion. There is also no record of work focusing on the detection and segmentation of the penumbra zone, a region that presents a high probability of recovery if identified and medicated quickly and correctly. Moreover, TIA does not receive the focus it merits from the researchers. Although it is a transient and reversible alteration it can be a warning sign of an imminent ischemic stroke. In many cases doctors are not able to distinguish a stroke from a TIA before the symptoms appear. Neuroimaging such as CT and MRI are not made for this type of accident, but there is a type of MRI, called diffusion weighted imaging (DWI), which can show areas of brain tissue that are not working and thus help to diagnose TIA. A potential research would be the location of the TIA, the affected area and the severity of the accident.

VI. Conclusion

In recent years, the number of people who have suffered a stroke has grown exponentially, and is becoming a serious public health problem worldwide. The use of new technology to aid medical diagnoses and during treatment optimizes patient outcomes. Neuroimaging is essential because it provides comprehensive information on cerebral and vascular health, and based on clinical assessments it serves to answer specific questions that improve decisions to choose the most appropriate treatment. However, the correct analysis of neuroimaging is essential for planning the treatment and implementation of a successful therapy. CAD systems have become an important research topic because they help in the interpretation of these images, increasing the accuracy of the diagnosis and improving inter- and intra-reader variability. The use of DIP and AI techniques in CAD systems has shown promising results, making them a fundamental tool to aid diagnoses and medical follow-ups. However, the development of these systems is still an open problem. Besides, these systems pass for long regulatory processes until approval. Therefore the use of these newly developed products do not follow the evolution of the state-of-the-art techniques. The rapid development of research for the detection, segmentation and classification of strokes contrasts with the long process that the CAD systems need for approval.

This review addresses the main methodologies and techniques of DIP and AI used in the development of CAD systems to aid stroke detection, segmentation and classification in various neuroimaging modalities. The main contribution is that this review has only considered very recent works, between 2015 and 2018, that address several modalities of image exams. The works listed here used not only classic DIP tools, but also advanced techniques of AI, ML and Deep Learning, and with various levels of automation. The publicly available databases were analyzed and characterized by exposing relevant information to researchers who encountered the lack of CT and MRI sets with their report. In the articles that used private databases we tried to present the execution settings of the exams and the equipment used in the acquisition of the images, which was not always possible due to a lack of technical information. In general, the papers used a small number of slices of each exam, selecting the best quality and attributes that could facilitate the detection, segmentation or classification, which could bias and compromise the results. We observed that most systems were developed for a particular stroke type or only had efficient applications and results in certain settings of time of occurrence, noise level, preprocessed image and mode of the examination. There were few reports of research with the aim to identify the subtypes of each category. The TIA, although it is a type of alert that must be taken seriously because it can indicate the probability of occurrence of a stroke, is rarely differentiated or even commented on. Among all the articles that met the inclusion requirements only 8.73%, i.e., 9 articles included stroke type identification, segmentation and classification in their subtypes and only 4 used CT exams, which is the standard examination for diagnosis. On the other hand, development in hardware and software in MRI has evolved rapidly and MRI-DWI has a relevant clinical use for the differential diagnosis of brain lesions. Other imaging technologies, such as the MWI system, which presents low cost and possible portability, are presented as a new option and had a relevant presence in the three areas of the scope of this review.

Among the ML techniques used, the SVM, the Bayes classifier and the FCM cluster technique are the most used and the ones with the more satisfactory results. The techniques of deep learning show up as a future trend, and even with the high training costs, CNN appears as a good potential and can serve as a preliminary step in a CAD system. The performance of the systems was evaluated based on the results of accuracy, sensitivity, specificity, precision and F-Score. Also the JSC, MCC and DSC metrics were used to indicate the degree of similarity in the lesions in comparative analyzes. However, the ideal is to use a metric that has a specific meaning for the task in question. The above metrics are important and can be used in a general way. For some papers we noted that there are better alternatives and more appropriate metrics for the context, which could also be applied to some of the ways to present the comparative analyses and results. Some works only showed the side-by-side segmentation results with the ground truth which is not a good form of visualization to ensure that the statements made in the research are consistent with the reality.

Use of wearable and IoT technology are two realities that are constantly developing and have received much attention from both the academia and the industry due to their potential use in very diverse areas of human activities including medicine. Virtual reality (VR) and augmented reality (AR) can aid in the planning and execution of surgical procedures, allowing visualization of organs in 3D and with the possibility of manipulating the organs virtually for a better visualization of the process. However, we did not find much research in these subjects. While such environments are quite adequate, some of them are expensive to design and maintain. Devices such as Kinect seem to be changing this scenario, since beyond the field of medications and hospital treatment, post-stroke treatment requires sessions of physiotherapy for an indeterminate time, and that is where patients and physiotherapists find the support of technologies associated with VR and AR. Similarly, we believe that smartphones and tablets will begin to play an important role in the future, since electronic health research kits are constantly being developed and monitoring patients at home seems to be the most promising direction. With the advancement of computational intelligence techniques CAD systems will certainly attract more importance and acceptance of the regulatory organs, both for the diagnosis and for the medical follow-up after treatment. There is still open field to use other techniques and integrate them into more complex and complete systems. For example, segmentation of brain injury with three-dimensional analysis, identification and segmentation of the penumbra zone, use of VR and AR for visualization and analysis of several types of neuroimaging are other spaces to be explored. However, this does not mean that the role of doctors and neuroradiologists will be assumed by such intelligent systems, these systems serve as a complement to clinical validation.

References

[1] J. Mackay, G. A. Mensah, and K. Greenlund, *The Atlas Heart Disease and Stroke*. Geneva, Switzerland: World Health Org., 2004. [Online]. Available: https://apps.who.int/iris/handle/10665/43007

[2] "Global atlas on cardiovascular disease prevention and control," World Health Org., World Heart Federation, World Stroke Org., 2011. [Online]. Available: https://www.who.int/cardiovascular_diseases/publications/atlas_cvd/en/

[3] American Heart Association and American Stroke Association, "What are the types of stroke?" Accessed: Jan. 26, 2016. [Online]. Available: http://www.strokeassociation.org/STROKEORG/AboutStroke/About-Stroke_UCM_308529_SubHomePage.jsp, Apr. 2016.

[4] World Health Organization, "Tobacco or health: A global status report," Geneva, Switzerland, 1997. [Online]. Available: http://www.cdc.gov/tobacco/who/whofirst.htm

[5] World Health Organization *et al.*, "Global health estimates: Deaths by cause, age, sex and country, 2000–2012. Geneva, WHO, 2014," *Google Scholar*, 2015.

[6] *Global Status Report on Alcohol and Health*. Geneva, Switzerland: World Health Org., 2014. [Online]. Available: https://apps.who.int/iris/bitstream/handle/10665/112736/9789240692763_eng.pdf?sequence=1

[7] Mozaffarian, "Heart disease and stroke statistics-2015 update: A report from the american heart association (vol 131, pg e29, 2015)," *Circulation*, vol. 131, no. 24, pp. E535–E535, 2015.

[8] D. Mozaffarian *et al.*, "Heart disease and stroke statistics-2016 update," *Circulation*, vol. 133, no. 4, pp. e38–e360, 2016.

[9] E. J. Benjamin *et al.*, "Heart disease and stroke statistics-2017 update: A report from the american heart association," *Circulation*, vol. 135, no. 10, pp. e146–e603, 2017.

[10] S. Mendis, *Global Status Report on Noncommunicable Diseases*. Geneva, Switzerland: World Health Organization, 2014.

[11] World Health Organization *et al.*, "Global action plan for the prevention and control of noncommunicable diseases 2013–2020. Geneva: WHO, 2013," *Public Health England. Interactive map–NHS health check*. Available: www.healthcheck.nhs.uk/interactive_map, 2016.

[12] W. N. Kernan, B. Ovbiagele, and S. J. Kittner, "Response to letter regarding article, 'Guidelines for the prevention of stroke in patients with stroke and transient ischemic attack: A guideline for healthcare professionals from the american heart association/american stroke association'," *Stroke*, vol. 46, no. 4, pp. e87–e89, 2015.

[13] S. B. de Doenças Cerebrovasculares *et al.*, "Primeiro consenso brasileiro do tratamento da fase aguda do acidente vascular cerebral," *Arq Neuropsiquiatr*, vol. 59, no. 4, pp. 972–980, 2001.

[14] U. Hanning *et al.*, "CT versus MR techniques in the detection of cervical artery dissection," *J. Neuroimaging*, vol. 27, no. 6, pp. 607–612, 2017.

[15] Y. Iyama *et al.*, "Iterative reconstruction designed for brain CT: A correlative study with filtered back projection for the diagnosis of acute ischemic stroke," *J. Comput. Assisted Tomography*, vol. 41, no. 6, pp. 884–890, 2017.

[16] L. Bonanno, S. Marino, P. Bramanti, and F. Sottile, "Validation of a computer-aided diagnosis system for the automatic identification of carotid atherosclerosis," *Ultrasound Med. Biol.*, vol. 41, no. 2, pp. 509–516, 2015.

[17] Y. Uchiyama *et al.*, "Computer-aided diagnosis scheme for detection of lacunar infarcts on mr images," *Academic Radiol.*, vol. 14, no. 12, pp. 1554–1561, 2007.

[18] T. M. Buzug and D. Mihailidis, "Computed tomography: From photon statistics to modern cone-beam CT," *Med. Phys.*, vol. 36, no. 8, pp. 3858–3858, 2009.

[19] R. I. Grossman and D. M. Yousem, *Neuroradiology: The Requisites*. Maryland Heights, MO, USA: C.V. Mosby Company, 2003.

[20] K. M. Waterstram-Rich and D. Gilmore, *Nuclear Medicine and PET/CT E-Book: Technology and Techniques*. London, U.K.: Elsevier Health Sci., 2016.

[21] G. L. Zeng, *Image Reconstruction: Applications in Medical Sciences.* Berlin, Germany: Walter de Gruyter GmbH & Co KG, 2017.

[22] H.-Y. Wey, V. R. Desai, and T. Q. Duong, "A review of current imaging methods used in stroke research," *Neurological Res.*, vol. 35, no. 10, pp. 1092–1102, 2013.

[23] M. Aswendt, J. Adamczak, and A. Tennstaedt, "A review of novel optical imaging strategies of the stroke pathology and stem cell therapy in stroke," *Frontiers Cellular Neuroscience*, vol. 8, p. 226, 2014.

[24] E. Goceri, E. Dura, and M. Gunay, "Review on machine learning based lesion segmentation methods from brain mr images," in *Proc. 15th IEEE Int. Conf. Mach. Learn. Appl.*, IEEE, 2016, pp. 582–587.

[25] G. Litjens *et al.*, "A survey on deep learning in medical image analysis," *arXiv:1702.05747*, 2017.

[26] H. Fujita *et al.*, "State-of-the-art of computer-aided detection/diagnosis (CAD)," in *Proceedings of the International Conference on Medical Biometrics* (Lecture Notes Comp. Sci. 6165), D. Zhang and M. Sonka, Eds. Berlin, Germany: Springer, 2010, pp. 296–305. [Online]. Available: https://doi.org/10.1007/978-3-642-13923-9_32

[27] J. J. Fenton *et al.*, "Influence of computer-aided detection on performance of screening mammography," *New England J. Med.*, vol. 356, no. 14, pp. 1399–1409, 2007.

[28] S. Astley and F. J. Gilbert, "Computer-aided detection in mammography," *Clin. Radiol.*, vol. 59, no. 5, pp. 390–399, 2004.

[29] M. J. G. Calas, B. Gutfilen, and W. C. d. A. Pereira, "CAD and mammography: Why use this tool?" *Radiologia Brasileira*, vol. 45, no. 1, pp. 46–52, 2012.

[30] H. Fujita *et al.*, "Computer-aided diagnosis: The emerging of three cad systems induced by japanese health care needs," *Comput. Methods Programs Biomed.*, vol. 92, no. 3, pp. 238–248, 2008.

[31] N. M. Saad, S. Bakar, A. S. Muda, and M. M. Mokji, "Review of brain lesion detection and classification using neuroimaging analysis techniques," *J. Teknologi*, vol. 74, no. 6, pp. 73–85, 2015.

[32] E.-S. A. El-Dahshan, H. M. Mohsen, K. Revett, and A.-B. M. Salem, "Computer-aided diagnosis of human brain tumor through MRI: A survey and a new algorithm," *Expert Syst. Appl.*, vol. 41, no. 11, pp. 5526–5545, 2014.

[33] J. A. Ludwig and J. N. Weinstein, "Biomarkers in cancer staging, prognosis and treatment selection," *Nature Rev. Cancer*, vol. 5, no. 11, p. 845, 2005.

[34] T. Inoue *et al.*, "Diagnosis of small posterior fossa stroke on brain CT: Effect of iterative reconstruction designed for brain CT on detection performance," *Eur. Radiol.*, vol. 27, no. 9, pp. 3710–3715, 2017.

[35] R. Gomolka, R. Chrzan, A. Urbanik, R. Kazmierski, A. Grzanka, and W. Nowinski, "Quantification of image contrast of infarcts on computed tomography scans," *Neuroradiology J.*, vol. 30, no. 1, pp. 15–22, 2017.

[36] D. R. Pereira, P. P. Reboucas Filho, G. H. de Rosa, J. P. Papa, and V. H. C. de Albuquerque, "Stroke lesion detection using convolutional neural networks," in *Proc. Int. Joint Conf. Neural Netw.*, IEEE, 2018, pp. 1–6.

[37] K. Sudharani, T. Sarma, and K. S. Prasad, "Brain stroke detection using k-nearest neighbor and minimum mean distance technique," in *Proc. Control Instrum. Commun. Comput. Technol.*, IEEE, 2015, pp. 770–776.

[38] D. Guo *et al.*, "Automated lesion detection on MRI scans using combined unsupervised and supervised methods," *BMC Med. Imag.*, vol. 15, 2015, Art. no. 50.

[39] E. A. Stamatakis and L. K. Tyler, "Identifying lesions on structural brain images-validation of the method and application to neuropsychological patients," *Brain Lang.*, vol. 94, no. 2, pp. 167–177, 2005.

[40] M. L. Seghier, A. Ramlackhansingh, J. Crinion, A. P. Leff, and C. J. Price, "Lesion identification using unified segmentation-normalisation models and fuzzy clustering," *Neuroimage*, vol. 41, no. 4, pp. 1253–1266, 2008.

[41] A. Sanju´an *et al.*, "Automated identification of brain tumors from single MR images based on segmentation with refined patient-specific priors," *Frontiers Neurosci*., vol. 7, 2013, Art. no. 241, doi: 10.3389/fnins.2013.00241.

[42] G. C. O'Connell *et al.*, "Machine-learning approach identifies a pattern of gene expression in peripheral blood that can accurately detect ischaemic stroke," *NPJ Genomic Medicine*, vol. 1, 2016, Art. no. 16038.

[43] E. P. Giri, M. I. Fanany, A. M. Arymurthy, and S. K. Wijaya, "Ischemic stroke identification based on EEG and EOG using id convolutional neural network and batch normalization," in *Proc. Int. Conf. Adv. Comput. Sci. Inf. Syst.*, IEEE, 2016, pp. 484–491.

[44] I. Bisio, A. Fedeli, F. Lavagetto, G. Luzzati, M. Pastorino, A. Randazzo, and E. Tavanti, "Brain stroke detection by microwave imaging systems: Preliminary two-dimensional numerical simulations," in *Proc. IEEE Int. Conf. Imag. Syst. Techn.*, IEEE, 2016, pp. 330–334.

[45] Y. Wu, M. Wang, and S. Ye, "A compact ultra-wideband antenna for stroke detection," in *Proc. IEEE Int. Conf. Microw. Millimeter Wave Technol.*, vol. 2, IEEE, 2016, pp. 546–548.

[46] J. Lee, S. Lee, and J. Choi, "Design of an antenna for brain stroke localization," in *Proc. URSI Asia-Pacific Radio Sci. Conf.*, IEEE, 2016, pp. 1265–1267.

[47] M. N. Stevanovic, R. Scapaticci, and L. Crocco, "Compressive sensing techniques for brain stroke monitoring," in *Proc. 10th Eur. Conf. Antennas Propag.*, IEEE, 2016, pp. 1–4.

[48] E. Ricci, S. Di Domenico, E. Cianca, and T. Rossi, "Artifact removal algorithms for stroke detection using a multistatic mist beamforming algorithm," in *Proc. 37th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, IEEE, 2015, pp. 1930–1933.

[49] E. J. Bond, X. Li, S. C. Hagness, and B. D. Van Veen, "Microwave imaging via space-time beamforming for early detection of breast cancer," *IEEE Trans. Antennas Propag.*, vol. 51, no. 8, pp. 1690–1705, Aug. 2003.

[50] M. Salucci, J. Vrba, I. Merunka, and A. Massa, "Real-time brain stroke detection through a learning-by-examples technique-an experimental assessment," *Microw. Opt. Technol. Lett.*, vol. 59, no. 11, pp. 2796–2799, 2017.

[51] Y. Wu, X. Xu, and M.-D. Zhu, "Subspace pattern recognition method for brain stroke detection," *Progress Electromagn. Res. Lett.*, vol. 64, pp. 119–126, 2016.

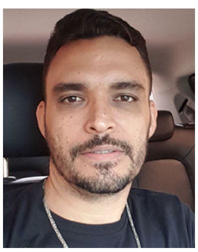
[52] M. Shokry and A. Allam, "Planar spiral antenna for brain stroke detection," in *Proc. 9th Eur. Conf. Antennas Propag.*, IEEE, 2015, pp. 1–4.

[53] M. Shokry and A. Allam, "UWB antenna for brain stroke and brain tumour detection," in *Proc. 21st Int. Conf. Microw. Radar Wireless Commun.*, IEEE, 2016, pp. 1–3.

[54] B. de Haan, P. Clas, H. Juenger, M. Wilke, and H.-O. Karnath, "Fast semi-automated lesion demarcation in stroke," *NeuroImage Clin.*, vol. 9, pp. 69–74, 2015.

[55] P. Clas, S. Groeschel, and M. Wilke, "A semi-automatic algorithm for determining the demyelination load in metachromatic leukodystrophy," *Academic Radiol.*, vol. 19, no. 1, pp. 26–34, 2012.
[56] E. Hajimani, M. Ruano, and A. Ruano, "MOGA design for neural networks based system for automatic diagnosis of cerebral vascular accidents," in *Proc. IEEE 9th Int. Symp. Intell. Signal Process.*, IEEE, 2015, pp. 1–6.
[57] M. Ruano, E. Hajimani, and A. Ruano, "A radial basis function classifier for the automatic diagnosis of cerebral vascular accidents," in *Proc. Global Med. Eng. Phys. Exchanges/Pan Amer. Health Care Exchanges*, IEEE, 2016, pp. 1–4.
[58] E. Hajimani, M. Ruano, and A. Ruano, "An intelligent support system for automatic detection of cerebral vascular accidents from brain CT images," *Comput. Methods Programs Biomed.*, vol. 146, pp. 109–123, 2017.
[59] F. Aghaei *et al.*, "Implementation of a computer-aided detection tool for quantification of intracranial radiologic markers on brain CT images," *Proc. SPIE*, vol. 10138, 2017, Art. no. 1013805.
[60] N. Bhadauria, M. Bist, R. Patel, and H. Bhadauria, "Performance evaluation of segmentation methods for brain CT images based hemorrhage detection," in *Proc. 2nd Int. Conf. Comput. Sustain. Global Develop.*, IEEE, 2015, pp. 1955–1959.
[61] M. Sun, R. Hu, H. Yu, B. Zhao, and H. Ren, "Intracranial hemorrhage detection by 3d voxel segmentation on brain CT images," in *Proc. Int. Conf. Wireless Commun. Signal Process.*, IEEE, 2015, pp. 1–5.
[62] E. D. S. Rebouças, A. M. Braga, R. M. Sarmento, R. C. Marques, and P. P. Rebouças Filho, "Level set based on brain radiological densities for stroke segmentation in ct images," in *2017 IEEE 30th Int. Symp. Comput Based Med. Syst.*, IEEE, 2017, pp. 391–396.
[63] A. F. Z. Yahiaoui and A. Bessaid, "Segmentation of ischemic stroke area from ct brain images," in *Proc. Int. Symp. Signal Image Video Commun.*, IEEE, 2016, pp. 13–17.
[64] O. Maier *et al.*, "ISLES 2015-A public evaluation benchmark for ischemic stroke lesion segmentation from multispectral MRI," *Med. Image Anal.*, vol. 35, pp. 250–269, 2017.
[65] O. Maier, C. Schröder, N. D. Forkert, T. Martinetz, and H. Handels, "Classifiers for ischemic stroke lesion segmentation: A comparison study," *PloS One*, vol. 10, no. 12, p. e0145118, 2015.
[66] R. Karthik and R. Menaka, "A multi-scale approach for detection of ischemic stroke from brain MR images using discrete curvelet transformation," *Measurement*, vol. 100, pp. 223–232, 2017.
[67] J. C. Griffis, J. B. Allendorfer, and J. P. Szaflarski, "Voxel-based Gaussian naïve Bayes classification of ischemic stroke lesions in individual t1-weighted MRI scans," *J. Neuroscience Methods*, vol. 257, pp. 97–108, 2016.
[68] A. Purushotham *et al.*, "Apparent diffusion coefficient threshold for delineation of ischemic core," *Int. J. Stroke*, vol. 10, no. 3, pp. 348–353, 2015.
[69] O. Maier, M. Wilms, J. von der Gablentz, U. M. Krämer, T. F. Münte, and H. Handels, "Extra tree forests for sub-acute ischemic stroke lesion segmentation in mr sequences," *J. Neuroscience Methods*, vol. 240, pp. 89–100, 2015.
[70] B. Machner *et al.*, "Impact of dynamic bottom-up features and top-down control on the visual exploration of moving real-world scenes in hemispatial neglect," *Neuropsychologia*, vol. 50, no. 10, pp. 2415–2425, 2012.
[71] B. Machner, I. Konemund, A. Sprenger, J. von der Gablentz, and C. Helmchen, "Randomized controlled trial on hemifield eye patching and optokinetic stimulation in acute spatial neglect," *Stroke*, vol. 45, no. 8, pp. 2465–2468, 2014.
[72] J. von der Gablentz, "Visuelle exploration von dynamischen szenen bei schlaganfallpatienten mit neglect-syndrom," Ph.D. dissertation, Zentrale Hochschulbibliothek Lübeck, 2013.
[73] D. Chyzhyk, R. Dacosta-Aguayo, M. Mataró, and M. Graña, "An active learning approach for stroke lesion segmentation on multimodal MRI data," *Neurocomputing*, vol. 150, pp. 26–36, 2015.
[74] A. K. Subudhi, S. S. Jena, and S. K. Sabut, "Delineation of infarct lesions by multi-dimensional fuzzy c-means of acute ischemic stroke patients," in *Proc. Int. Conf. Elect. Electron. Signals Commun. Optim.*, IEEE, 2015, pp. 1–5.
[75] M. K. Nag *et al.*, "Computer-assisted delineation of cerebral infarct from diffusion-weighted MRI using gaussian mixture model," *Int. J. Comput. Assisted Radiol. Surgery*, vol. 12, no. 4, pp. 539–552, 2017.
[76] R. Zhang *et al.*, "Automatic segmentation of acute ischemic stroke from DWI using 3D fully convolutional densenets," *IEEE Trans. Med. Imag.*, vol. 37, no. 9, pp. 2149–2160, Sep. 2018.
[77] L. Chen, P. Bentley, and D. Rueckert, "Fully automatic acute ischemic lesion segmentation in DWI using convolutional neural networks," *NeuroImage Clin.*, vol. 15, pp. 633–643, 2017.
[78] H. Noh, S. Hong, and B. Han, "Learning deconvolution network for semantic segmentation," in *Proc. IEEE Int. Conf. Comput. Vision*, 2015, pp. 1520–1528.
[79] D. Pustina, H. Coslett, P. E. Turkeltaub, N. Tustison, M. F. Schwartz, and B. Avants, "Automated segmentation of chronic stroke lesions using linda: Lesion identification with neighborhood data analysis," *Human Brain Mapping*, vol. 37, no. 4, pp. 1405–1421, 2016.
[80] P. Jayaram and R. Menaka, "An experimental study of Stockwell transform-based feature extraction method for ischemic stroke detection," *Int. J. Biomed. Eng. Technol.*, vol. 21, no. 1, pp. 40–48, 2016.
[81] T. Achiha *et al.*, "Voxel-based lesion mapping of cryptogenic stroke in patients with advanced cancer: A detailed magnetic resonance imaging analysis of distribution pattern," *J. Stroke Cerebrovascular Diseases*, vol. 26, no. 7, pp. 1521–1527, 2017.
[82] P. Sivakumar and P. Ganeshkumar, "An efficient automated methodology for detecting and segmenting the ischemic stroke in brain MRI images," *Int. J. Imag. Syst. Technol.*, vol. 27, no. 3, pp. 265–272, 2017.
[83] Y. Wu, M. Zhu, D. Li, Y. Zhang, and Y. Wang, "Brain stroke localization by using microwave-based signal classification," in *Proc. Int. Conf. Electromagn. Adv. Appl.*, IEEE, 2016, pp. 828–831.
[84] C. R. Gillebert, G. W. Humphreys, and D. Mantini, "Automated delineation of stroke lesions using brain CT images," *NeuroImage Clin.*, vol. 4, pp. 540–548, 2014.
[85] M. Sajjadi *et al.*, "A promising method of enhancement for early detection of ischemic stroke," *J. Res. Med. Sci. Official J. Isfahan Univ. Med. Sci.*, vol. 17, no. 9, p. 843, 2012.
[86] R. McKinley *et al.*, "Fully automated stroke tissue estimation using random forest classifiers (FASTER)," *J. Cerebral Blood Flow Metabolism*, vol. 37, no. 8, pp. 2728–2741, 2017.
[87] N. D. Forkert, T. Verleger, B. Cheng, G. Thomalla, C. C. Hilgetag, and J. Fiehler, "Multiclass support vector machine-based lesion mapping predicts functional outcome in ischemic stroke patients," *PloS One*, vol. 10, no. 6, p. e0129569, 2015.
[88] P. P. Rebouças Filho, R. M. Sarmento, G. B. Holanda, and D. de Alencar Lima, "New approach to detect and classify stroke in skull CT images via analysis of brain tissue densities," *Comput. Methods Programs Biomed.*, vol. 148, pp. 27–43, 2017.
[89] P. P. Rebouc¸as Filho, E. D. S. Rebouc¸as, L. B. Marinho, R. M. Sarmento, J. M. R. Tavares, and V. H. C. de Albuquerque, "Analysis of human tissue densities: A new approach to extract features from medical images," *Pattern Recognit. Lett.*, vol. 94, pp. 211–218, 2017.
[90] R. Jeena and S. Kumar, "Analysis of stroke using texture features," in *Proc. Int. Conf. Control Commun. Comput*, India, IEEE, 2015, pp. 366–370.
[91] G. Ostrek, A. Nowakowski, M. Jasionowska, A. Przelaskowski, and K. Szopiński, "Stroke tissue pattern recognition based on CT texture analysis," in *Proc. 9th Int. Conf. Comput. Recognit. Syst.*, Springer, 2016, pp. 81–90.
[92] B. Shahangian and H. Pourghassem, "Automatic brain hemorrhage segmentation and classification algorithm based on weighted grayscale histogram feature in a hierarchical classification structure," *Biocybernetics Biomed. Eng.*, vol. 36, no. 1, pp. 217–232, 2016.
[93] A. Subudhi, U. R. Acharya, M. Dash, S. Jena, and S. Sabut, "Automated approach for detection of ischemic stroke using Delaunay triangulation in brain MRI images," *Comput. Biol. Med.*, vol. 103, pp. 116–129, 2018.
[94] K. Chellappan *et al.*, "MR image enhancement for ICH classification," in *Proc. IEEE EMBS Conf. Biomed. Eng. Sci.*, IEEE, 2016, pp. 160–165.
[95] M. Hopfer, R. Planas, A. Hamidipour, T. Henriksson, and S. Semenov, "Electromagnetic tomography for detection, differentiation, and monitoring of brain stroke: A virtual data and human head phantom study," *IEEE Antennas Propag. Mag.*, vol. 59, no. 5, pp. 86–97, Oct. 2017.
[96] S. Semenov, M. Hopfer, R. Planas, A. Hamidipour, and T. Henriksson, "Electromagnetic tomography for brain imaging: 3d reconstruction of stroke in a human head phantom," in *Proc. IEEE Conf. Antenna Meas. Appl.*, IEEE, 2016, pp. 1–4.

[97] P.-H. Tournier *et al.*, "Microwave tomography for brain stroke imaging," in *Proc. IEEE Int. Symp. Antennas Propag. USNC/URSI Nat. Radio Sci. Meeting*, IEEE, 2017, pp. 29–30.
[98] C. M. Dourado Jr., S. P. P. da Silva, R. V. M. da Nóbrega, A. C. d. S. Barros, P. P. Rebouças Filho, and V. H. C. de Albuquerque, "Deep learning IoT system for online stroke detection in skull computed tomography images," *Comput. Netw.*, vol. 152, pp. 25–39, 2019.
[99] K. Ameer and K. Ali, "iPad use in stroke neuro-rehabilitation," *Geriatrics*, vol. 2, no. 1, p. 2, 2017.
[100] J. Libove, D. Schriebman, M. Ingle, and B. Wahl, "Wearable brain imager/BMI technology for structural, vascular and functional extraction," in *Proc. IEEE Int. Conf. Syst. Man Cybern.*, IEEE, 2016, pp. 003806–003811.
[101] A. Hassan *et al.*, "Using a portable device for online single-trial MRCP detection and classification," in *Proc. Int. Conf. Intell. Data Eng. Automated Learn.*, Springer, 2015, pp. 527–534.
[102] D. Dutta, S. Modak, A. Kumar, J. Roychowdhury, and S. Mandal, "Bayesian network aided grasp and grip efficiency estimation using a smart data glove for post-stroke diagnosis," *Biocybernetics Biomed. Eng.*, vol. 37, no. 1, pp. 44–58, 2017.
[103] J. R. Villar, S. González, J. Sedano, C. Chira, and J. M. Gabriel-Trejo-Galan, "Improving human activity recognition and its application in early stroke diagnosis," *Int. J. Neural Syst.*, vol. 25, no. 04, 2015, Art. no. 1450036.



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