A Survey of Stroke Image Analysis Techniques

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Abstract. Stroke is one of the instantaneously shocking and spiking cerebrovascular diseases having substantial residual effects. Image analysis techniques have the ability to diagnosing and providing proper treatment for stroke patients. To lighten the problem, various techniques of image analysis have been proposed. Thus, this survey intended to analyze these proposed image analysis approaches intending to thoroughly examine the state-of-the-art image analysis techniques. To prepare this survey, the systematic literature review method was employed. Based on the reviewed literature, several clinical and biological image datasets are found to be used in the process of stroke diagnosis. However, there are very few publicly accessible datasets are available currently. In this survey, each image analysis technique used for stroke image analysis processes is briefly discussed. Finally, open research challenges are identified that could be addressed in the future.

Keywords: Image analysis · Systematic literature review · Stroke image analysis

1 Introduction

Stroke is one of instantaneously shocking and spiking cerebrovascular diseases having substantial residual effects. Globally, 15 million people suffer from stroke each year [1]. Among these, five million die and another five million are left permanently disabled placing a burden on family and community. Stroke is also one of the publicly and widely known reason for death and disability around the globe [2]. The stroke burden in Africa, including Ethiopia, is likely to increase because of demographic changes and the inadequate control of major risk factors for stroke including hypertension, cardiac disease, obesity, diabetes, and smoking [3]. Basically, the two commonly known types of strokes are Ischemic and Haemorrhagic strokes. When an artery is congested in our brain it causes ischemic stroke. Whereas, a broken blood vessel causes a Haemorrhagic stroke. Recently, the concept of artificial intelligence is being incorporated into many fields, including health and medicine to provide potent tools that aid professional decision making processes. Artificial intelligence techniques such as Machine Learning had become popular tools for inferring medical images to recognize various forms of imaging information rendering medical diagnosis. Thus, we are motivated to provide this comprehensive review of image analysis techniques for stroke diagnosis in terms

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of current efforts and future directions. As a result, the following research questions are identified.

RQ1: How image analysis techniques and modalities are used for stroke imaging?
RQ2: What existing image analysis techniques are applied for stroke imaging?
RQ3: What datasets are available in stroke image analysis?

The main aim of this survey is to identify the state-of-the-art in image analysis techniques as applied in stroke diagnosis and the dataset being used thereof. Specifically,

– To identify and compare the applicability of image analysis techniques and imaging modalities on stroke disease management (diagnosis).
– To analyze and assess the state-of-the-art in image analysis techniques as applied to stroke imaging.
– To find out and show open research challenges for further study.

2 Methodology

This survey work adopted the structured literature review approach to examine the application of image analysis techniques and modalities in stroke diagnosis and management. For finding the entire population of scientific papers that are relevant to the identified research questions, proper searching strategies was employed on six different electronic databases such as Google Scholar, Archivx, IEEE Xplore, Springer, PubMed and Web of Science. The research string patterns used were: ("STROKE DIAGNOSIS") AND ("IMAGING TECHNOLOGIES") AND ("STROKE IMAGE ANALYSIS TECHNIQUES") AND ("IMAGING MODALITIES OR STROKE IMAGING MODALITIES") AND ("APPLICATION OF IMAGE ANALYSIS TECHNIQUES IN STROKE DIAGNOSIS"). Totally the search retrieved 81 papers, among which unduplicated and relevant papers in terms of the research questions are 76. The inclusion and exclusion criteria are summarized in Table 1.

Table.1 Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
Type of studies Journals, Conf. Proc., and Book Chapters that are published on peer-review basis	− Short papers, experience reports, summaries of workshops, & papers in the form of abstracts, tutorials, or talks
Documents in the area of stroke image analysis techniques	− Documents in the area of image analysis that do not deal with the techniques
Documents in the area of imaging modalities applied to stroke	− Documents in the area of image analysis that mention analysis techniques as an example but do not discuss in detail
The scientific material that has been published since 2004	− Documents that do not match the search string
	− Studies with low relevance to the RQs
	− Studies that do not fulfill the inclusion criteria

Table.2 Study selection

Database	Round One	Round Two	Used	Excluded
IEEE Explore	11		8 (72.73%)	3 (27.27%)
Springer	16	3	9 (47.36%)	7 (52.63%)
Google scholar	8		2 (25%)	6 (75%)
Archivx	12		3 (25%)	9 (75%)
Web of science	7		1 (10%)	6 (90%)
PubMed	22	2	7 (29.17%)	17 (29.83%)
Total	76	5	30 (37.04%)	51 (62.96%)

As shown in Table 2, two different rounds have been used to identify the relevant works. Firstly, 76 non-redundant works were identify for further evaluation. After a critical evaluation of these papers, extra five papers are obtained from the citations. Finally, however, only 30 papers are considered for review in this work. Table 3 shows those selected studies arranged in order.

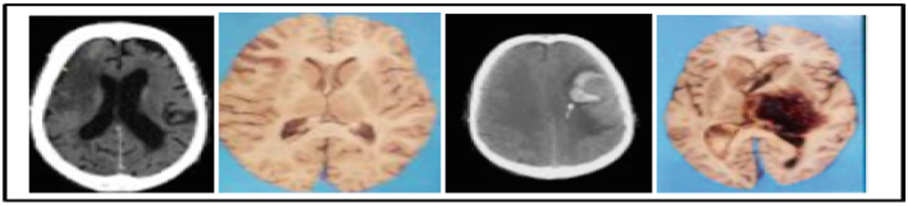
Table.3 List of article identifiers

Id.	**Ref.**	**Id.**	**Ref.**	**Id.**	**Ref.**	**Id.**	**Ref.**	**Id.**	**Ref.**
P1	[1]	P7	[8]	P13	[16]	P19	[22]	P25	[32]
P2	[2]	P8	[9]	P14	[17]	P20	[24]	P26	[33]
P3	[3]	P9	[10]	P15	[18]	P21	[26]	P27	[34]
P4	[5]	P10	[11]	P16	[19]	P22	[29]	P28	[35]
P5	[7]	P11	[13]	P17	[20]	P23	[30]	P29	[36]
P6	[8]	P12	[14]	P18	[21]	P24	[31]	P30	[37]

The rest of this report is organized as follows. The section that follows, section three, discussed stroke imaging modalities and section four highlighted stroke image analysis techniques and related works. Finally, open challenges and gaps that have not yet been fully addressed in existing works are summarized.

3 Stroke Diagnosis

In stroke diagnosis process there are three main phases, viz., clinical diagnosis, laboratory diagnosis, and imaging [30, 67]. The clinical diagnosis phase is the first step used to check weather a patient has a stroke or not through an assessment of symptoms. Symptoms of a stroke can be different for different people. The most common symptoms of stroke includes speaking trouble, paralysis, seeing problem of one or both eyes, headache and walking problems. In laboratory diagnosis phase, blood testing is conducted. Complete blood count and clotting time tests are performed in this phase. These tests are used to know the level of platelets and how quickly the blood clots, respectively. The third phase is imaging. It is used to identify which type of stroke is occurred in the patient (Fig. 1).



a) Ischemic stroke b) Haemorrhagic stroke

Fig. 1. Stroke images [4]

3.1 Stroke Imaging Modality

Basically, screening a patient with stroke disease is to decide whether the patient is feeling an ischemic or Haemorrhagic stroke in order to give the right treatment. The two known stroke imaging modalities are discussed as follows [6].

3.1.1 Computed Tomography (CT)

It is a way of scanning internal body with multiple scenes through essential x-ray tools integrated with computers. Using CT scan, experts can identify a stroke from a blood clot or bleeding within the brain. CT scan tests show abnormalities in the brain, and can aid to determine if these parts are caused by inadequate blood flow (ischemic stroke), a burst blood vessel (haemorrhage), or a different kind of problem [7]. In contrast to other techniques, CT and Magnetic Resonance Imaging (MRI) scans can display the internals of the head showing the details of soft tissues, bones, brains and blood vessels. It is a primary method of determining whether a stroke is ischemic or haemorrhagic. It is also used to show other attributes of brain defects such as spots and sizes influenced through extra factors like cancers, and clots, among others.

3.1.2 Magnetic Resonance Imaging (MRI)

MRI uses a potent magnetic field, radio frequency pulses and a computer to yield detailed images of organs, soft tissues, bone and almost all other internal body structures. It is among the most known and high level tools used to give the required image viewing including three dimensional (3D) views. Mostly, this tool is used for medical purposes. It works without using any rays unlike computed tomography replacing the rays by magnets that provide strengths as high as 20,000 times. It could be managed using appropriate tools or machines with internal instructions that help them capture images, displaying appropriate body parts or tissues showing their internal workings as needed [12].

3.1.3 Advancements in Stroke Imaging Modalities and Associated Performance Evaluation Metrics

Image analysis processes require imaging modalities and techniques to analyze stroke images by capturing the targeted body parts using MRI or CT scan devices. Advancements are observed with both modalities.

Table.4 Summary of stroke imaging modalities with sensitivity and time onset of symptoms

Sensitivity	Time	Stroke type	Modalities	Citation
100%	>3 h	Hemorrhagic	CT (CTA, CTP)	[40, 44, 47]
86%–90%	>6 h	Hemorrhagic		
93%	<48 h	Hemorrhagic		
17%–58%	>48 h	Hemorrhagic		
64%–85%	>3 h	Ischemic		[40, 47]
47%–80%	>6 h	Ischemic		
23%–81%	<48 h	Ischemic		
53%–74%	>48 h	Ischemic		
–	>3 h	Hemorrhagic	MRI (MRA, MRP, DWI)	[44, 45]
86%–90%	>6 h	Hemorrhagic		
46%	<48 h	Hemorrhagic		
38%–97%	>48 h	Hemorrhagic		
–	>3 h	Ischemic		[45, 47]
65%	>6 h	Ischemic		
84%–88%	<48 h	Ischemic		
94%-98%	>48 h	Ischemic		

Key: CTA = Computed Tomography Angiography, CTP = Computed Tomography Perfussion, MRA = Magnetic Resonance Angiography, MRP = Magnetic Resonance Perfussion, DWI = Deffusion Weithed Imaging

Recently, studies were conducted on MRI modalities showing its various advancements to stroke imaging as discussed in [17, 18, 20, 23]. CT has also shown advancements as addressed in previous studies [19, 21, 22]. There are several performance evaluation metrics of imaging modalities. Among these metrics, some of them are discussed in Table 4. In the Table, the most known stroke imaging modalities such as CT and MRI are examined based on their range of sensitivity with the time onset of stroke symptoms for both Haemorrhagic and Ischemic stroke types.

4 Image Analysis

The process of image analysis has grown dramatically as its applicability increased on several fields of science and technology. The main points with image analysis is improving the visual quality of an image to extract useful information or features based on different image properties such as color, gloss, morphology of the objects, and texture [13]. Figure 2 depicts the main steps of image analysis.

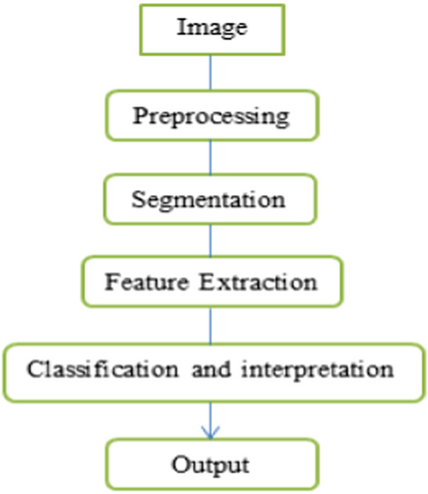


Fig. 2. Image analysis steps [13]

4.1 Image Analysis Techniques

Since image analysis is used as a tool for recognizing, differentiating, and quantifying various types of images it involves, on each step of analysis, various computing techniques.

4.1.1 Pre-processing

In image analysis pre-processing is the term for operations on images at the lowest level of abstraction. These operations do not increase image information content but they decrease it if entropy is an information measure. The aim of pre-processing is an improvement of the image data that suppresses undesired distortions or enhances some image features relevant for further processing and analysis task. There are 4 different types of Image Pre-Processing techniques such as;

- *Pixel brightness transformations (PBT)* [13, 68]: which is used to modify pixel brightness and the transformation depends on the properties of a pixel itself. In PBT, output pixel's value depends only on the corresponding input pixel value.
- *Gamma correction* [13, 68]: it is a non-linear adjustment to individual pixel values. While in image normalization we carried out linear operations on individual pixels, such as scalar multiplication and addition/subtraction, gamma correction carries out a non-linear operation on the source image pixels, and can cause saturation of the image being altered.
- *Image Filtering and Segmentation* [13, 68]: The goal of using filters is to modify or enhance image properties and/or to extract valuable information from the pictures such as edges, corners, and blobs. A filter is defined by a kernel, which is a small array applied to each pixel and its neighbors within an image
- *The Fourier Transform* [13, 68]: it is an important image processing tool which is used to decompose an image into its sine and cosine components. The output of the

transformation represents the image in the Fourier or frequency domain, while the input image is the spatial domain equivalent. In the Fourier domain image, each point represents a particular frequency contained in the spatial domain image [68].

4.1.2 Segmentation

The crucial step in image analysis processes is segmentation. It is a method used to divide an image into its constituent parts or segments having similar features [14]. The reason behind using segmentation technique is to identify the object of interest that depends on the specified application constraints. Since the main goal of image segmentation is to separate images in to its constituent parts, identifying and using the appropriate image segmentation technique is very important. There are two different image segmentation types such as local segmentation and global segmentation. Local segmentation deals with image's local properties which are characterized by the interactions of neighboring pixels and the image edge. It is also deals with particular region of image only. While, the mean values of different pixel classes and the continuous boundary of the region are the focus of global segmentation. Global segmentation also concentrated by partitioning overall image poses highest amount of pixels. The most popular image segmentation techniques are discussed below.

– *Thresholding Method:* it is one of the common image segmentation methods preferred based on our prior knowledge of image features to identify the lighter front object from the background images. It has three varieties as global, variable and multiple thresholding. In global thresholding the threshold values are constant or not changed. In variable thresholding the threshold values can vary over the image. While in multiple thresholding values are used to compute the correct result in multiple thresholding [14, 15]. In global thresholding, the threshold values are constant or not changed.

$$\mathrm{q}(\mathrm{x},\mathrm{y}) = \begin{Bmatrix} 1,\ \mathit{if}\ p(\mathrm{x},\mathrm{y}) > T \\ 0,\ \mathit{if}\ p(\mathrm{x},\mathrm{y}) \le T \end{Bmatrix} \tag{1}$$

Adapted from [15]

In variable thresholding, the threshold values can vary over the image. While, values are used to compute the correct result in multiple thresholding [14, 15].

$$\mathrm{q}(\mathrm{x}\ ,\mathrm{y}) = \begin{Bmatrix} m,\ \mathit{if}\ p(\mathrm{x}\ ,\mathrm{y}) > T1 \\ n\ \mathit{if}\ p(\mathrm{x},\mathrm{y}) \le T1 \\ o\ \mathit{if}\ p(\mathrm{x}\ ,\mathrm{y}) \le T0 \end{Bmatrix} \tag{2}$$

Adapted from [15]

– *Edge Based Method:* it is an edge detection technique used based on the quick fluctuation of intensity of the image. This happens because it is difficult to have useful details of edges using a single value of intensity. The first step in edge based segmentation techniques is detecting all edges and then connecting them together for the sake of making boundaries of that object. This properly scatters the required image portions [15, 16].

– *Region Based Method:* as its name implies, this technique is the key image segmentation used for segmenting the image depending on pixel similarity properties. It can be classified into region growing and split & merge methods. Region growing methods are used for segmenting the image into several regions based on the growth of seeds. That means, firstly, it groups image pixels that are selected from the original image. Second, after selecting the similarity criteria feature sets it grows regions by appending together those seeds or pixels that have similar predefined properties. It finally, stops the region growing process when there is no more inclusion criteria to be achieved [16, 17].
– *Clustering Based Method:* It is a process of organizing groups of image pixels based on their attributes. Usually, a group of similar pixels fit a region being different from others creating a cluster [16].

4.1.3 Feature Extraction

A feature of an image is the basic identification property. Having a big sized image needs more time to analyze. Accordingly, in order to have an easy and quick analysis process it is mandatory to have the required quantitative details of the object. Through identifying the portion required for analysis, it is possible to minimize the computational requirements of detecting objects. This further enhances its efficiency.

Features can be categorized as low level and high level features. Since a low-level feature is extracted directly from the source image, it is quite different from the high-level one. On the other hand, the extraction of high-level features is based on those low-level features [19, 20].

Handcrafted features have been used for more than a decade in a number of computer vision applications, including object detection and image classification. Over time, the number of features has increased to better adapt to the various tasks being tackled by researchers. Different types of the handcrafted features are used in machine learning approaches. Some of the most common types are; Local Binary Pattern (LBP) [35], Local Ternary Pattern (LTP) [36] and Local Phase Quantization (LPQ) [37]. Many state-of-the-art descriptors are based on LBP [38]. These approaches extract features that are general-purpose and are, therefore, most suitable for building a generic computer vision systems.

According to [35], LBP has rapidly become a popular descriptor mainly because of its low computational complexity and ability to code fine details. The canonical LBP operator [35] is computed at each pixel location by considering the values of a small circular neighborhood (with radius R pixels) around the value of a central pixel. One variant that has inspired many others is the Local Ternary Patterns (LTP), proposed by Tan and Triggs [36], which utilizes a 3-valued encoding scheme that includes a threshold around zero for the evaluation of the local gray-scale difference.

The LPQ operator, first proposed by Ojansivu and Heikkila [37], is based on the blur invariance property of the Fourier phase spectrum and uses the local phase information extracted from the 2-D short-term Fourier transform (STFT) computed over a rectangular neighborhood at each pixel position of the image.

4.1.4 Classification

Classification is one of the methods that comes after image feature extraction and segmentation. It helps us classify an image based on problem types. Image classification technique are applied for prediction and detection purposes in stroke diagnosis and management processes [1, 24–27].

4.2 Image Analysis Techniques for Stroke Diagnosis

Among the emerging image analysis techniques is machine learning approaches. In this section the most known machine learning techniques that are used for stroke diagnosis are briefly revised. Thus, the trends of image analysis is discussed based on their learning ability.

- *Manual image analysis:* there are several methods of image analysis applied in stroke diagnosis using traditional Machine Learning techniques. Basically, these machine learning processes are start with preprocessing. The next feature extraction step is followed using hand crafted methods and the final classification step is continued to classify normal and abnormal stroke slices. Accordinglly, some extracted features like intensity, texture and wavelet transform are inserted to the specific model as input. Those algorithms are limited in processing the natural images in their raw form, because they require expert knowledge and lots of time for tuning the features [48, 66].
- *Semi-automatic image analysis:* Since the advancement of image acquisition equipment are rapidly changing, the system's ability to come up with those tools is also enhanced. Thus, machine lerning techniques that are capable to learn features have emerged [48]. In semi-automatic analysis, the system can learn features and perform its own activities, but it needs expert support to learn and accomplish the needed tasks [48, 66].
- *Automatic image analysis:* It is an emerging trend of machine learning approaches that are capable of reducing or eleminating experts support completely. In this method, the machine has the ability to learn each feature automatically. Some machine learning approaches can apply automatic learning techniques. Currently, among the most known automatic image analysis techniques is deep learning [26, 48]. It has minimized the challenges faced in conventional machine learning approaches in the analysis of complex images like those found in medical domains which are subjective, and error prone.

Deep learning algorithms such as Convolutional Neural Network (CNN), Recurrent neural Network (RNN), Long-Short-Term Memory (LSTM), Extreme Learning Model (ELM), Generative Adversarial Networks (GANs) and the likes are fed with raw data, have automatic features learning ability that is done considerably faster [26]. These algorithms can learn multiple levels of abstractions, representations and information automatically from large set of images that exhibit the desired behavior of data [26, 48]. The most popular techniques that are being used for stroke image analysis are discussed as follows.

4.2.1 Convolutional Neural Networks (CNNs)

It is a type of neural network that effectively performs image classification and recognition. It is also used to automatically detect important features without any human intervention. There are three different layers in a CNN; convolutional, pooling and fully connected layers. In order to build a fully functional CNN architecture those different layers should be stacked. CNNs are one of the best learning algorithms for understanding image content and have shown exemplary performance in image segmentation, classification, detection, and retrieval tasks [62]. In CNN, there are many different types of architectures identified based on their own purposes. Some of the most popular CNN architectures are;

- *LeNet-5* [34, 62]: it is the first architecture of CNN produced to overcome the drawbacks of image recognition. The main motivations of this model includes shared weight ideas and back propagation optimization with neural networks. It plays a great role by introducing CNN with its full layers.
- *AlexNet* [34, 62]: the emergence of this architecture reduces the problems with large margin and scale recognition with tasks of detecting an object. It was the initial point for computer vision concepts because it deals with large complex datasets. It is different from LeNet-5 by its ability to provide ReLU (Rectified Linear Unit) and DropOut in CNN.
- *GoogleNet* [34, 62]: it is also called Inception. It was developed by the team of Google Brain. It contributes by reducing the number of parameters needed to implement CNNs.
- *VGGNet* [34, 62]: it is a well known neural network identified in ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2014. It is primarily used in image localization and image classification purposes.
- *ResNet* [34, 62]: supports the idea that very deep classical CNNs are harder to optimize mostly due to the vanishing gradient problem. To solve this challenge, the new residual block was introduced in this model.
- *Xception* [34, 62]: it is a.k.a. Extreme Inception model. It achieved better results than ResNet on big Google dataset called JFT, through verifying the concept of correlation with cross channels that could be decoupled from corelations of spatial data.
- *NasNet* [34, 62]: this model explores the hypothesis that is possible to create an efficient learning architecture directly from dataset of interest.

4.2.2 Recurrent Neural Networks (RNNs)

RNN is empowered with recurrent connections which enable the network to memorize the patterns form last inputs. The fact that the Region of Interest (ROI) in medical images which is usually distributed over multiple adjacent slices, as in CT or MRI, results in having correlations in successive slices. Accordingly, RNNs are able to extract inter-slice contexts from the input slices as a form of sequential data. The most popular types of RNNs are:

- *Long Short-Term Memory (LSTM):* is an architecture of recurrent neural network used in deep learning approaches. The main diffirentiating feature of LSTM from standard feed forward neural networks is the occurence of feedback connections. It has the ability to process both single image and entire sequences of data. The reason behind the creation of LSTM is to overcome the problem of gradient vanishing that occur while training traditional RNNs. It is also used to add new useful information and erase the previously saved memory [63].
- *Gated Recurrent Unit (GRU):* it is similar with LSTM by its erase (forgete) gate. But, it has very limited number of parameters. The reason for that is it lacks an output gate. It also perform well in less frequent and small datasets. But it could not perform good in unbounded counting unlike LSTM. This makes it fail to learn some languages that could be simple for LSTM [60].

4.3 Related Works

Various studies are employed on medical imaging throughout the world previously. But, the intention, application area, approaches used and scope of those studies varies accordingly. Among the employed several works on this area, most of them are concentrated on both Machine Learning and Deep Learning based image analysis techniques used for stroke diagnosis as seen and discussed here below separately.

4.3.1 Machine Learning Based Stroke Image Analysis

The machine learning approaches have been applied in several types of medical image analysis including stroke disease diagnosis. The main intention of this section is to review the relevant related works of machine learning techniques applied on stroke diagnosis and treatments. In stroke image analysis process different stages are there as we have seen previously. As a result there is various machine learning studies have been employed on stroke imaging. Those studies were concentrated mostly on the detection and prediction tasks by using image analysis pathways such as; segmentation, feature extraction and classification. Here below, the related works on machine learning approaches for stroke detection and stroke prediction are reviewed and discussed as follows.

In [18], the study aims to provide appropriate approach used for assisting the physician during stroke diagnosis. As a main problem, the rising medical mistakes specifically for stroke diagnosis were mentioned in this study. To overcomming this problem the study proposed the accurate way used for stoke diagnosis. Accordingly, the segmentation method was used for imaging brain stroke by using MRI devices for capturing the required images. For the sake of writing and implimenting the program the MATLAB tool with its own language was also used to achieve the good result through having clear images with more details for the brain. Finally in this study, fifteen (15) images of brain stroke with thresholding and morphological segmentation methods were used. There is no any evaluation metrices are used and mentioned on this study.

In [19], the automatic detection mechanism of stroke disease was proposed through using CT images. According to the study, selecting appropriate features from large datasets were challenging. As a result the proposed approach, collecting 92 extracted features and overcame the problem existed with selection complexity. Thus, the proposed particle swarm optimization (PSO) method was used for the 98 brain CT images. Finally SVM (Support Vector Machine) was employed for testing purposes. The study performed a good result of 92% accuracy by comparing with previous studies.

In [20], since the accurate classification of the stroke section with problems is needed for aids quick diagnosis processes, this study came with stockwell transform based method used for detecting ischemic stroke. The proposed study concentrated to diagnosis or detection of ischemic stroke in the brain. In this study, the SEA (Skull Elimination Algorithm), CLSA (Central Line Sketching Algorithm), FCM (Fuzzy C-Means), and DOST (Discrete Orthonormal Stockwell Transform) were used for extracting the tissue part only in the brain, spliting the MR image qually, extracting the lession part, and extracting the features like mean, median and standard deviation respectivelly. In this study 20 MR images samples with 2D view of axes were used for expriment, and implimented by using MATLAB tool. The evaluation results of the proposed approach was not mentioned in this study.

In [23], the study for detecting stroke diseases by using segmentation and classification methods were proposed. The study aims to automatically segmenting and classifying stroke diseases through using DWI imaging modality. The 3D image was constructed to view the captured imagein three different axes. Fuzy C-means method was used for segmenting the image and the spatial features were also extracted from the region of interest. The rule based method was used to classify the extracted features. In this study both acute and chronic lesion are analyzed to achieve accuracy results 90% and 70% respectively. The study performed the overall sensitivity and specifity results of 84.38% and 83.33% for the classification respectively. The image samples of 30 acute and 20 chronic slices were used with MATLAB analysis tool here.

In [28], the ways of detecting ischemic stroke using DWI images was proposed for stroke diagnosis. This proposed way is working automatically through using computer aided system. The stroke detection process consists both segmentation and classification methods. The expectation maximization approaches were used for segmentation issue. The classification activities concentrated to classify into partial and total anterior circulation syndrome and lacunar syndrome stroke using random forest classifier method. Once the part of affected image region was segmented, the remaining process is followed by using FODPSO (Fractional-Order Darwinian Particle Swarm Optimization) technique. In this study, 192 MRI scan for evaluation was used. The study achieved 94.3%, 92% and 94% of accuracy, sensitivity and dice similarity index results respectively. Finally, the challenging activity of determining the 3D volumetric value of lesions was recommended as a future works of line.

In [49], the problem of cerebral edema to the deterioration of neurology and death after stroke was mentioned. Also, the lack of effective ways of preventing and predicting the occurrence of the disease accurately were presented. The study deals with an automation of imaging the brain in order to attain proper volumetric data saved for big stroke patient's repository. CT was used as a modality in this study. A random forest segmentation approach with 400 CT images for testing purpose was used. A machine learning algorithm with the capability of segmenting and computing cerebrospinal fluid (CSF) volume from sequential CT scans of stroke patients could be created to support the proposed approach.

In [50], the main aim of this study was, to provide an efficient hybridization model able for the purpose of classifying MR brain image as normal and abnormal. Accordingly, for the sake of extracting features the digital wavelet transform was used. For decreasing the feature space the principal PCA was used. Finally for the parameter optimization kernel support vector machine and radial basis function kernel was used. The performed results were; 98.79% sensitivity, 96.29% specificity, 98.65% accuracy.

Some relevant works have been conducted on forecasting or predicting stroke disease risks and the mortality rates by using classification algorithms with the machine learning ways such as; DT (Decision Tree), NN (Neural Network) and NB (Naive Bayes) with various useful attributes. In [52], the study aims to identify weither or not the ischemic stroke location and infraction volume helps the prediction processes related to functional outcome was proposed. Here, a multi class SVM technique with 68 MR images of ischemic stroke was used. The proposed study score good result comparatively than conventional methods.

In [53], the study concentrated on improving the prediction efficiency of stroke risk classification by using machine learning algorithms was proposed. The proposed study used two steps to doing the required activities. The datasets used for training and testing purposes were first developed using both under and over sampling techniques. Then some other methods were created to classify stroke levels of risk. Such methods are; DT, NN, NB, LR (Logistic Regression), RF (Random Forest), BN (Bayesian Network) and both voting and boosting models. The study attain 99.94%, 97.33% and 98.44% boosting model recall with DT, RF based precision and recall respectively.

As shown here, most of the studies employed on diagnosis and prognosis purposes only through using image analysis processes. Which means [18–20, 23, 28, 38, 49, 50] deals with stroke diagnosis and some studies [52, 53] were intended to the issue of prognosis. This indicates that, there is no works aimed to provide stroke treatment and used for prevalence issues in this regard. The accuracy result of those previous studies shows that, all works employed by using 3D images [23, 49] were performed poor results than those used 2D images [19, 28, 50].

This indicates, analyzing stroke images with 3D views were challenging activities for conventional machine learning techniques. In addition, only little work was conducted with stroke image registration and retrieval techniques. Registration of stroke images is a common image analysis task in which a coordinate transform is calculated from one image to another. This ignored process is very useful for clinical issues of experimental design. Several types of modalities have the ability to imaging; this might deserve its own role for facilitating the process of health care. Currently, the size of accumulated images are growing dramatically, this extracted images could be collected globally in any information system developed for the purpose of health care services. But there is no adequate works available regarding this in stroke imaging.

Table.5 Summary of existing machine learning image analysis techniques applied for stroke imaging

Ref.	For	Process	Mod	Type	Technique	Size	DM	Acc.
[17]	Dia	SG	MRI	B-Stroke	TR	–	2D	–
[19]	Dia	FE	CT	Ischemic	PSO + SVM	98	2D	92%
[20]	Dia	SG + FE + CL	MRI	Ischemic	SEA,CLSA,FCM + DOST	20	2D	–
[23]	Dia	SG + CL	DWI	B-Stroke	FCM	50	3D	90%
[28]	Dia	SG	MRI	Ischemic	EM-FODPSO	192	2D	94.3%
[38]	Dia	RG	CT	Ischemic	TR	37	2D	–
[49]	Dia	SG	CT	Ischemic	RF	400	3D	–
[50]	Dia	FE + CL	MRI	B-Stroke	DWT + K-SVM + R-SVM	–	2D	98.65%
[52]	Pro	CL	MRI	Ischemic	Multi-class SVM	68	–	85%
[53]	Pro	PR	–	Stroke	RF	–	–	99.94%

Key: Acc = Accuracy, B-Stroke = Brain Stroke, CL = Classification, Dia = Diagnosis, DM = Dimension, DWT = Digital Wavelet Transform, EM = Expectation Maximization, FE = Feature Extraction, K = Kernel, Mod = Modality, PR = Prediction, Pro = Progonosis, PSO = Particle-swarm optimization, R = Radial, RG = Registration, SG = Segmentation, TR = Thresholding

4.3.2 Deep Learning Based Stroke Image Analysis

Since this study is concerning with image analysis techniques, the most relevant deep learning based studies for stroke imaging are reviewed and discussed here below. In [54], the proposed study aims to detect ischemic stroke disease by using image analysis technique. Here, the main problems of manual segmentation processes were mentioned and novel automatic method was proposed for overcoming problems. Automatic segmentation process with FCNN (Fully Convolutional Neural Network) was used to segment CTP images with 2D view. Since it could be provide contextual information publicly, the model with PSPNet (Pyramid-Scene-Parsing Network) was used in this study. For learning different and challenging shapes the concept of focal function was also used. The proposed study achieved the DSC (Dice Similarity Coefficient) result of 0.54%.

In [55], this study proposed the detection of ischemic stroke through segmenting lesion from images. The CNN approaches with DenseUnet model was used for successful segmentation purposes in this study. The multi-modal MR modalities with 2D image views also applied for imaging the required brain part. The overall dataset size used in the study was totally 94 samples, which means 83 training and 11 validation samples. The proposed study achieved 0.635% with a DSC result finally.

In [56], another study aims to detecting ischemic stroke disease by using the segmentation processes with PCNet model. This new model was proposed to overcome the challenges with multi-modality, occurrences and the small size of the image to segmenting lesion automatically. The study used CNN approaches and 304 multi-modal MR images with 3D views were collected. The proposed study was performs 0.902% of DSC result.

In [57], the proposed study aims detecting ischemic stroke by using CNN approaches. The imaging modality used with the proposed study was CTA and the image captured has three dimensional views. Totally 60 image samples were collected, which are 30 training samples and 30 testing images. The highest result of DSC was 0.61 for the proposed approaches.

In [34], the concept of an IoT (Internet of Things) is presented this study. As a method, the CNN approach with Machine Learning classifiers was used to identifying a brain into a normal, ischemic stroke or hemorrhagic stroke. Totally 800 image samples were used here using CT imaging modality. The idea behind transfer learning was also applied here through integrated with other machine learning techniques. The intention of this study is detecting the stroke online without any challenge. As stated in the paper, the system performed 100% accuracy. But the proposed work is limited to 2D images. It is also challenging to deal with big 3D datasets.

In [50], there is also another study conducted for the purpose of detecting acute ischemic stroke automatically using CTA images. For this purpose a model that was very sensitive to change is proposed for the balance between hemispheres of the brain. An experiment is conducted to show the capability of the proposed model regarding the structure of the brain. The proposed study achieves good AUC (Area Under Curve) result of 0.914%. Generally for this study, deep symmetry sensitive network and convolutional neural network model was utilized with 217 image samples.

According to [58], the concept of detecting ischemic stroke using semi-supervised learning strategy was proposed. In this study an automatic segmentation process was applied. The CNN approach with DPC-Net (Double Path Classification Network) model was proposed to do the given task. Herewith the study, 460 image samples with 3D views could be collected using MR imaging modality. The DSC performance of the proposed study was 0.642%.

In [25], the study proposed the automatic lesion outcome prediction for stroke disease based on deep learning approaches. The study used other clinical information in addition to MR images. The study aims to create a CNN-UNet model with awareness of collateral and principal dynamics of blood flows. Here, only 75 image samples were collected using MR imaging modality. These images are limited to 2D views. The proposed study was achieved below the expert performances of the 0.58% DSC result.

In [59], here is also another study conducted to forecast the functional outcome of thrombectom. The approach used for directly exploiting data with multi-modal ways. The comparative assessments were used in between unimodal and multimodal images for the sake of having good functional outcome prediction results. Finally the proposed study attained with 0.75% of AUC results. Most of the reviewed studies were used the concept of data augmentation to obtain large image sizes as we have seen in the table below. Accordingly in [51], the current advances in data-augmentation techniques applied to MRI of brain were discussed. The pros and cons of data-augmentation technique are also described. Accordingly, the main challenges or limitation of data augmentation are mentioned. Since the data augmentation methods are able to overcoming the overfitting challenges, it is also very time consuming, generative adversarial networks applicable only in training-time, and it can easily concentrate multiple similar samples.

To conclude, several studies have been explored the image analysis approaches for the purpose of solving stroke problems. Related and relevant studies applied on stroke disease are reviewed and well discussed in this section. As the previous works achieved good results on their application area, they have different own limitations also. Generally, the absence of large stroke dataset; best analysis technique used for stroke imaging with small size dataset, and the absence of proper studies conducted for providing treatments for stroke patients are the main limitations of existed deep learning based image analysis techniques for stroke imaging. For solving the problem of dataset size, the augmentation method have been applied in [54, 60, 61, 64, 65]. But, it could not shows proper changes in the performance result.

4.4 Summary of Stroke Image Analysis Techniques

Basically, in this section some interesting notions of existed stroke image analysis techniques, the approaches used for stroke imaging and their application areas were discussed. Thus, machine learning and deep learning approaches with image analysis processes such as segmentation, feature extraction, classification, detection and prediction were widely used in stroke image analysis researches. In both Tables 5 and 6, the existing machine learning and deep learning based image analysis techniques applied in which stroke types, using which imaging modalities, approaches, dataset size, image dimension and the performed results were also shown in order to answer the research question 2. Based on the objectives of this survey, these existed analysis techniques are analyzed and examined, their limitations are also identified in this section.

Table.6 Summary of deep learning based image analysis for stroke imaging

App	Model	Technique	Type	Mod	DM	Size	Aug	DSC	Ref.
CNN	UNet	Prediction	Both	MR	2D	75	–	–	[25]
CNN	PSPNet	Segmentation	Ischemic	CTP	2D	–	Yes	0.54	[54]
CNN	Dense-UNet	Segmentation	Ischemic	MM-MR	2D	94	No	0.635	[55]
CNN	Res-FCN	Segmentation	Ischemic	MM-MR	2D	212	Yes	0.645	[65]
CNN	CNN + ML	Detection	Ischemic	CT	2D	800	No	–	[34]
CNN	PCNet	Segmentation	Ischemic	MM-MR	3D	304	No	0.902	[56]
CNN	3DCNN	Detection	Ischemic	CTA	3D	60	–	0.61	[57]
CNN	DeepSymNet	Detection	Ischemic	CTA	–	217	–	–	[50]
CNN	cGNA	Segmentation	Ischemic	MR, CT	–	–	Yes	–	[60]
CNN	DeepMedic	Segmentation	Ischemic	MRP	–	75	Yes	0.34	[61]
CNN	DPC-Net	Segmentation	Ischemic	MR	3D	460	No	0.642	[63]
CNN	AB-DNN	Segmentation	Ischemic	CTP	2D	–	No	–	[58]
CNN	ResNet-50	Segmentation	Ischemic	CT	3D	400	Yes	–	[63]
CNN	ClinicDNN	Prediction	Ischemic	CT	3D	400	–	–	[59]
CNN	MPFN	Segmentation	Ischemic	MR	3D	–	Yes	0.622	[62]

Key: AB = Attention-Based, App = Approach Aug = Augmentation, cGNA = Conditional Generative Adversarial Network, CilinicDNN = Clinical-Deep Neural Network, DeepMedic = Deep Medical, DeepSymNet = Deep Symetry Network, DM = Dimension, MM = Multimodal, MPF = Multi Plane Fusion, ResFCN = Residual-Fully-Convolutional-Network

4.5 Stroke Data Availability

In machine learning processes when large datasets are available, good results can be obtained. Since the severity of stroke diseases, there should be significant amounts of data available for MRI and CT globally [32]. Accordingly in stroke imaging semi- or fully-automated algorithms that uses machine learning techniques require training and testing on large datasets could be applicable for analyses purposes. Unfortunately a small number of imaging datasets have been made public in stroke imaging. Those that are available often were reached from a few institutions and do not reveal the variety of imaging devices and clinical scenarios that will be met in global settings. As a result, several studies employed small data sets available locally and publicly accessible datasets of stroke imaging. In Table 7 lists the available stroke image dataset that are mentioned in terms of size, format and image modality used.

Table.7 Summary of available stroke datasets

Dataset	Size	Format	Modality	Ref.
ATLAS	304	XML	MRI	[42]
FCP-INDI	229	–	MRI	[42]
I-KNOW	102	VOI	MRI	[41, 43]
ISLES	26	NIfTI	multi-modal MRI	[43, 55]
SFB	23	NIfTI	MRI	[41, 46]

Key: ATLAS = Anatomical Tracings of Lesions After Stroke, FCP-INDI = Functional Connectomes Project International Data Sharing Initiative, I-KNOW = Interconnected Knowledge database, ISLES = Ischemic Stroke Lesion Segmentation, SFB = Sonderforschungsbereich

5 Open Research Challenges

5.1 Challenges in Imaging Modalities

During the process of image analysis for stroke diagnosis, the problem of divergent occurrence of the required organ could be considered as a great challenge. That means, size of the tissue, shape and it's occurrence location of the organ that planned to capture may not similar for all patients [39].

The vague borderline through inadequate contrast among aiming tissues and the nearby tissues is considered as a recognized essential imaging challenge.

5.2 Challenges in Analysis Techniques

In recent approach, artificial intelligence model effectively applied in medical signal and image analysis in object identification and classification directly from images by eliminating the step to extract the features, thus speed-up the process of classification [32, 34]. The importance of automated segmentation technique is stated in many studies and also technically applied for different purposes. The segmentation of image that centered on deep learning techniques has got enormous consideration and it acmes the necessity of having an inclusive review of it recently.

Segmenting aimed tissue from complex volumetric images require a model used to extract features with deep and extreme information. However, the challenges with those 3D models are train deep networks to accomplish the desired goal accordingly.

5.3 Challenges in Dataset Availability

5.3.1 Constructing a Big Stroke Imaging Dataset

Since there is only few publicly available stroke datasets are existed, there is a gap on analyzing large and ever changing data easily for providing accurate and quick results. So, more effective data collection, identification, and management of stroke images methods will be needed for research that could be easily findable, accessible, interoperable and reusable. Imaging is the crucial step in brain stroke diagnosis [32]. Furthermore, even there is a lot of magnetic resonance imaging or computed tomography sequences consists many slices with a particular brain image, a massive amount of imaging data could be stored rapidly through medical practice. However, there is no properly stowed stroke image in various health care sectors. Once the patients are diagnosed, their history was removed rather than storing. This conveys the absence of large size stroke datasets. Thus, accommodated efforts will be needed across the health care sectors globally.

5.3.2 Developing a New Algorithm

Based on its necessities, constructing a big dataset for stroke imaging is mandatory. It also needs cooperative efforts worldwide to overcome challenges with standardization of imaging protocols, and development of a user-friendly repository, leading and controlling the developed repository.

For having large stroke dataset several studies were also proposed data augmentation methods. This data augmentation method is capable to generate artificial data from the original data. Conversely, image augmentation outputs are depends only on estimation, and decisions made based on these results must be treated accordingly. As depicted in the Table 6, the augmentation method have been applied in [54, 60, 61, 64, 65] but, there is no changes shown with their performance results. Hence, new algorithm which can be applicable for small size stroke image dataset will be needed.

5.3.3 Developing the Full-Fledged System Used for Stroke Diagnosis and Treatment

All previous studies were focused on stroke diagnosis and forecasting issues. Accordingly, the absence of proper works conducted for stroke treatment was one of the most perceived gaps. In previous studies, only images data was used for investigation. But, it is difficult to mine every diagnosis and treatment knowledge from image data only. Some data about stroke treatments, clinical and blood investigation could be collected from domain experts and related medical literatures.

Through combining the image data, blood laboratory results, clinical and treatments information it could be possible to develop a full-fledged system used for stroke diagnosis and treatment accurately. Such systems will be very important and performs best results in the developing countries like Ethiopia, where there is a lack of professional domain experts and poor medical infrastructures.

6 Conclusions

In this survey study we have identified and analyzed the various techniques of image analysis approaches. As a result, the state-of-the-art in image analysis techniques has been summarized and analyzed. Moreover, several clinical and biological image datasets are found being used in stroke diagnosis. And yet, much of these data sets are publicly accessible begging for open access datasets and repositories. Finally, the most common open research challenges in the area are identified and briefly discussed.

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