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"Transforming Healthcare with Ai: A Study on Medical Image Analysis"

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Abstract:
With the advancement of medical imaging techniques, an increasing number of medical images are being generated in healthcare facilities. Automated analytical systems are emerging as valuable databases, enabling efficient scanning and processing of medical images to create "big data." In this paper, we provide an overview of the evolution of machine learning methods, with a focus on the changing visual representation mechanisms in deep learning for recognition tasks. Specifically, we explore the applications of AI-image analysis in gastroenterology and herpetology, encompassing endoscopy, radiology, and pathology. These applications demonstrate the tremendous potential of AI in aiding medical professionals with accurate diagnosis, prognosis, and treatment strategies. By integrating AI technologies, radiologists can enhance their efficiency, allowing them to take on additional tasks that bring added value to patient care and strengthen their role in multidisciplinary clinical teams.
Keywords: Artificial Intelligence, Endoscopy, Radiology..

Introduction

Every day, the analysis of medical data grows, which makes it harder for people to analyze by hand and leads to more requests to do it automatically. To cut down on human errors, it is important to use some tools to automatically collect, sort, and analyze medical data. Using Artificial Intelligence (AI) techniques in medicine is helpful for storing and retrieving data and making the best decisions about how to use information analysis to solve problems. The fact that correct diagnosis and treatment of diseases are so important to healthcare systems makes medical imaging issues so hard to solve. Because of this, algorithms for automatic medical image analysis are used to help make medical images more reliable and easy to understand. Digital image processing and its combinations with other AI methods, such as machine learning, fuzzy logic, and pattern recognition, are so helpful when it comes to seeing and analyzing medical images. Intelligent methods can help with precise identification of biological features and accurate analysis.

Through techniques called "artificial intelligence," computers can act like smart people. Also, there are enough factors to look at and figure out what's wrong, which makes a doctor's job hard. The best way for an expert to find all the risk factors and show certain results in vague terms is to use a precise tool. In this thesis, there is a reason to design and build such a tool, which is based on artificial intelligence and can be used to diagnose tumors and other diseases. There is no one solution that works for all problems, and each solution works differently for each problem. So it's important to find a unique way of doing this that works well for a certain problem. In this thesis, different ways are used to automatically find brain tumors with an MRI and figure out their stage. The performance of each of the different approaches is compared to find the one that works best. In the process of diagnosis, doctors use their medical knowledge and MRI scans to figure out what's wrong with the tumors and how to treat them. When a patient's scans were taken more than once, the process of finding and separating things got boring. So, if you want to get out of this boring situation, you need computer-based detection and segmentation. The break is filled by a technique that uses artificial intelligence.

MRI data segmentation is the process of putting artificial intelligence to work. With an artificial method, tissues like gray matter, cerebrospinal fluid, white matter, and tumors can be found. It is very important for the MRI to automatically find problems. So, the neural networks and segmentation process accurately find different types of brain tumors. The difference between the target value and the real value was kept as small as possible. Ophthalmologists use images of the retina to find and diagnose many eye diseases. Some diseases, like glaucoma, diabetic retinopathy, and macular degeneration, are very dangerous because they can cause blindness if they aren't caught in time. So, retinal 2 image analysis has been a difficult area of research that tries to find techniques to help find and diagnose many eye diseases early on. Traditional techniques rely on manual observation, which is prone to mistakes. So, there is a very high need for automated technologies that can help find diseases. No matter what techniques are used, retinal images are required for this application. This is because abnormalities are easier to see in the retina than in any other part of the eye. The way blood vessels look in the retina is a very important part of figuring out what's wrong with the eye. The only place where blood vessels can be seen straight on is in the retina. Most retinal diseases don't affect the whole retina in their early stages. This means that vision loss happens more slowly. But if the disease is found and treated early, it can be slowed down or even stopped. The camera is usually used to take a picture of the retina, which is the back part of the eye. This image can be used to diagnose, treat, and evaluate different problems with the eye. Medical imaging has come a long way in the last few decades, and now doctors can look inside a person's body without hurting them in order to diagnose and treat them. With the development of medical imaging modalities that give doctors different ways to measure the structure and function of internal anatomy, doctors can now do common clinical tasks like diagnosing and keeping an eye on patients in a safer and more effective way than before. A few years ago, radiologists could only use a small number of techniques that did not hurt the patient. Clinical diagnostic imaging required a lot of experience and practice, as well as deep knowledge and even intuition. In recent years, this task has become much easier thanks to the improvement and development of many image acquisition techniques, the improvement of the overall quality of the images acquired, advances in image processing, and the development of large computational capacities.

One way to segment an image is to have a trained anatomist or technician who knows what they're doing mark some areas of interest by hand. Manual methods, on the other hand, take a lot of time. For example, labeling some or all of the structures in a high-resolution image of the brain can take up to a week. Also, manual or interactive segmentations, which are usually limited to 2D slice-by-slice processing, don't always work the same way from one slice to the next. Lastly, earlier studies have shown that manual segmentations have a lot of differences, which seems to increase the risks of inter- and intra-observer reliability. For quantitative analysis of medical images, you need segmentation methods that can be used again and again, are accurate, and work well. In order to get meaningful (i.e. statistically significant) results, it is often necessary to segment a large number of images. So, it's good to have automated segmentation. But the problem is that images are usually messed up because of things like image noise, uneven image intensity, and the partial volume averaging effect. In recent years, people have come up with and made a number of segmentation algorithms to deal with these unwanted artifacts that mess up the images. Even though these techniques produce accurate and repeatable results, only a few of them can guarantee that the segmentations they produce are true to the structures' real anatomy. Very often, the segmentations have small errors in their geometry that change how the modeled structures really look. In medical imaging, the overall shape of a region of interest is set by medical knowledge; it is usually known ahead of time. The results of segmentation techniques should be able to show how the structures are put together. Several clinical and research applications, such as visualization, surgical planning, surface-based processing of functional data, surface-based atlas, inter-subject registration, etc., depend on how accurate and correct the representations are. But it is hard to do accurate segmentation under anatomical consistency. Mathematically, "anatomical consistency" means that the shape is correct from a topological point of view. One of the problems is that topological ideas are continuous, which makes it hard to turn them into a practical, discrete framework that can be used to divide up medical images. Also, the anatomical consistency of segmentation refers to how the shape and its local properties fit together on a global scale. This idea, which is both local and global, is hard to model and work into the process of segmentation.

Literature Review

Xie et al. (2021) – A lot of progress has been made in computer-aided detection and diagnosis. It is used to treat cancers of the lung, breast, eyes, and skin. Small datasets hurt datasets like ImageNet, COCO, ChestXray14, and DeepLesion. Doctors' knowledge and experience, also called "domain knowledge," are added to these datasets to make them better. Natural datasets or other medical datasets are used to add more information. Datasets now include information about how doctors are trained and how they make diagnoses. Better data sets are used to find lesions.

Wiestler & Menze (2020) – In this paper, advances in deep learning have led to neural network algorithms that can classify and divide images better than humans can. Neurooncologists and computer scientists are working together to figure out how deep learning techniques. People study the parts that make up artificial neural networks like convolutional neural networks. Features of imaging like genotype are also talked about. Explains the things that make it hard to use algorithms widely.

Willemink et al (2020) Large, labeled datasets have made it possible to solve hard machine learning problems, like natural image recognition in computer vision, which can involve millions of images. Because of this, many people hope that similar progress will be made in medical applications. Eventually, algorithm research should solve a clinical problem that is posed as a discrimination task. Medical datasets, on the other hand, tend to be smaller, with hundreds or thousands of records: Share a list of sixteen "large open source medical imaging datasets," whose sizes range from 267 to 65,000 subjects. In medical imaging, we talk about the number of subjects. However, a single subject may have more than one image, for example, if they were scanned at different times. For the sake of simplicity, we'll assume that each subject has only one image or scan to look at.

Arimura et al (2019) Radiomics is a new way to get closer to precision medicine. It is one of the most advanced uses of AI in medical imaging research. There are two steps to radiochemistry. The first step is to pull out the features. Images from different sources could be used. To separate the volumes of interest, image segmentation algorithms are used. After the grouping, the features will be taken out. Some of the most common features are texture, geometry, tumor volume, shape, density, pixel intensity, and so on. The second step is to put the extracted features into mathematical models to decode the tumor's phenotype and predict how it will respond to treatment. If you can accurately predict the outcome, you can use that information to design more effective treatments. For example, lung cancer patients may have a lot in common, such as their age and how the cancer looks. But the images of the tumor might look different, and the length of time people live with the disease might be very different. If radiomics can take the image information, decode the phenotype, and then predict the survival time or prognosis before treatment, different treatment plans could be chosen. This is called personalized medicine or precision medicine. Biomarkers were used in the past to figure out a patient's prognosis or subtype, which usually required an invasive biopsy. For real-time tracking of the treatment area during delivery, the automatic fiducial/marker detection is needed. Most common ways to make a template require that you know the properties of the marker ahead of time.

Research Methodology

Numerical morphology is a tool for focusing on parts of a picture that help show and describe the shape of a place, like edges, skeletons, and curved bodies. The language of numerical morphology is situated theory, and it can be used to explain paired images: a point is either in the situated or it isn't, and the common set administrators might be linked to them. In scientific morphology, the most important operations work on two sets: the picture and the organizing component. In practice, the organizing element is usually a 3x3 grid, which is much smaller than the one in the picture. Binary operations are thought of as binary images, which are made from MR images that have been pre-processed. The same can be given by morphological filtering, which gives useful information about an image.

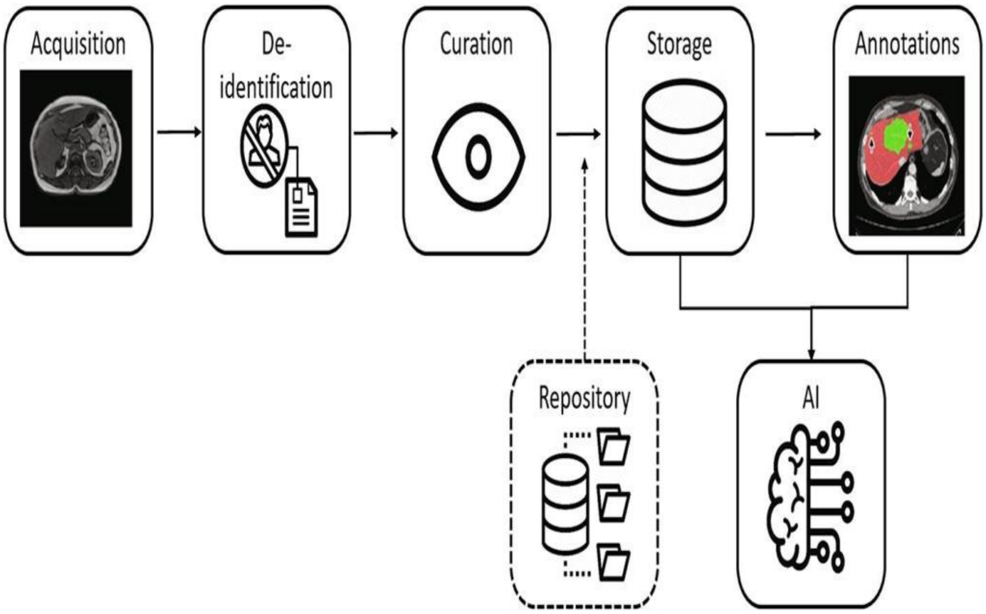


Figure 1. System Architecture

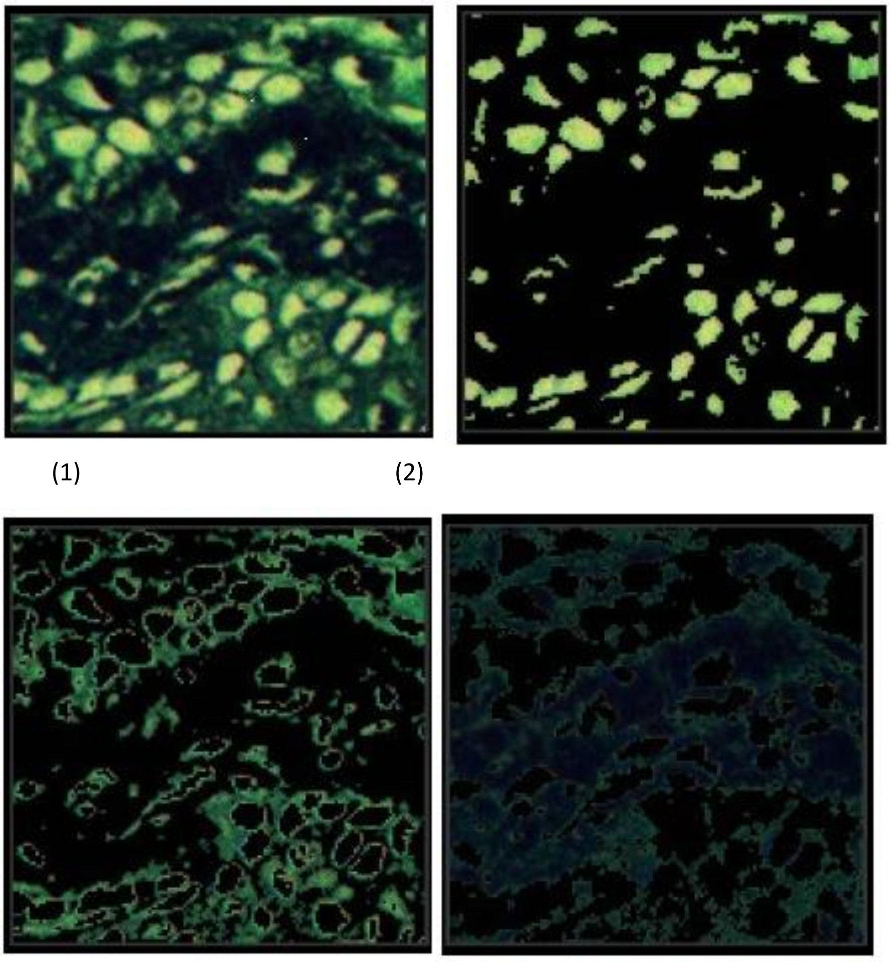
Features which are the characteristics of the objects of interest, show the most important information that a picture has to offer about a lesion if they are chosen correctly. Characteristic extraction techniques look at questions and pictures to find the most obvious tricks that show how different types of articles are alike. Classifiers use people's quirks as inputs to put them in the group that they belong to. The goal of peculiarity extraction is to reduce the amount of first-hand information by measuring the tricks that make one data design different from another. The focused feature should give the classifier the parts of the data type by taking into account how the important properties of the image are shown as trick vectors. In this proposed method, we separate the things that go with it.

Shape features include circularity, unpredictability, area, perimeter, and shape index. Intensity features include mean, variance, standard variance, median intensity, skewness, and kurtosis. Texture features include contrast, correlation, entropy, energy, homogeneity, group shade, and entirety of square difference.

Digital image negatives can be used for many things, like showing medical images or taking a picture of a screen with a monochrome positive film so that the negatives can be used as normal slides. Contract stretching is done to make the gray cells in the image being processed have a wider range of brightness and darkness. When the dynamic range of the processed image is much wider than what the display device can show, only the brightest parts of the image are shown. In automated image analysis, colour is a strong identifier that makes it easier to find objects and pull them out of a picture. Feature Selection is a method that is often used in machine learning. In this method, subsets of the tools available from the data are chosen to provide a learning calculation. The best subset has the fewest measurements that help with high correctness and measurements that don't matter. There are two parts to the characterization method: the preparation stage and the testing stage. During the preparation stage, facts that are already known are given. In the testing stage, unclear information is given, and the classifier is used to put things in the right order. How well the preparation goes will determine how right the order is. In more detail, after getting approval from the ethical committees at the clinical sites, data de-identification is the key to getting anonymous images and following local data protection laws. Then, data curation is needed to make sure that the data that goes with it, like the metadata in the image headers, is correct. Last but not least, medical annotations, such as anatomical boundaries and descriptions of lesions, are very important not only for training the AI algorithms but also for testing them.

Result Analysis

To test how well the proposed method works, a series of experiments are done with 120 sample images of squamous cell carcinoma of the esophagus, 40 from each of three categories: well-differentiated, moderately-differentiated, and poorly-differentiated. Figure 2 shows the three parts of an image made with fuzzy c-means clustering: the nucleus, the cytoplasm, and the background. The minimum distance classifier is used to find the area around the nuclei, and then morphological operations are used on this segmented image to get rid of the squared-off look around the nuclei (Figure 3(a) and (b)).

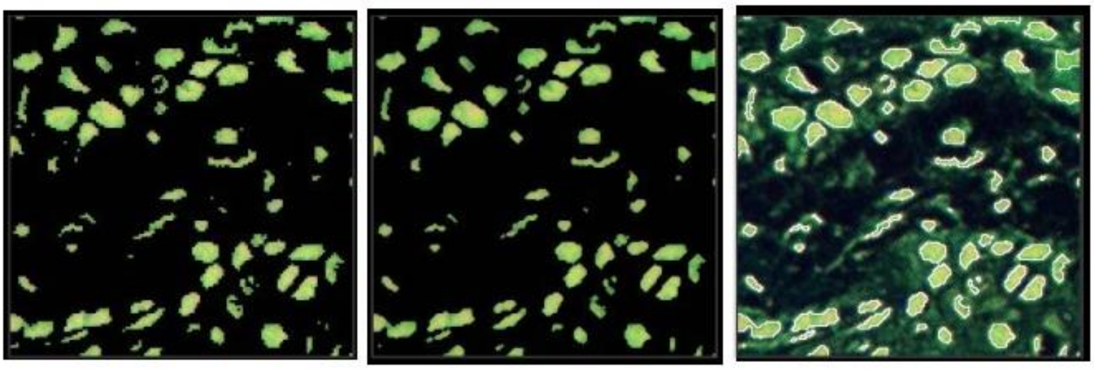


(1) (2)

(3) (4)

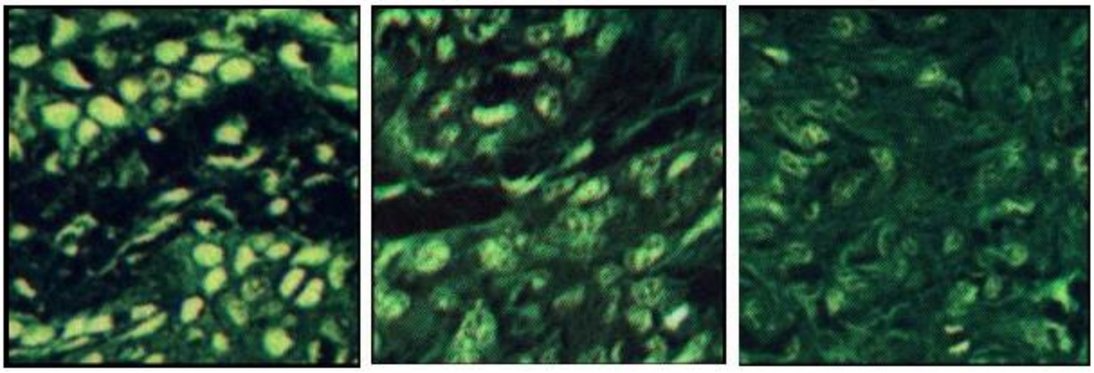
Figure 2 (1) Original microscopic colour image, (2) Nuclei region, (3) Cytoplasm region & (4) background region.

The results are compared with the manually segmented nuclei image in Figure 3. The segmentation done by hand by a medical expert agrees well with the results of the experiment. Figure 4 shows pictures of squamous cell carcinoma that is well differentiated, moderately differentiated, and not well differentiated.



(a) (b) (c)

Figure 3 (a) Identified cell nuclei image in Figure 2 (2), (b) Cell nuclei image after applying the morphological operations, and (c) Manual Segmentation of nuclei done by the medical expert.



(a) (b) (c)

Figure 4: The sample images of squamous cell carcinoma: (a) Well differentiated, (b) Moderately differentiated, and (c) Poorly differentiated.

For poorly differentiated squamous cell carcinoma, the classification is correct 100% of the time. Five test sample images are used to get a classification accuracy of 75% for well-differentiated squamous cell carcinoma and 62.5% for moderately-differentiated squamous cell carcinoma. But a more accurate classification could be made by using a large number of test images from the same biopsy of a patient.

Conclusion

The thesis focuses on the analysis of endoscopic images of the lower esophagus to detect abnormal areas and identify cancerous growth. Various color image segmentation techniques have been developed to automatically identify cancerous regions in endoscopic images, thereby facilitating quicker and more accurate disease diagnosis and treatment. Experimental studies using endoscopic image datasets and comparisons with manual segmentation by medical experts have demonstrated the effectiveness of these methods. The segmented images are intended to aid medical experts in obtaining precise biopsy samples from the identified pathological lesions. However, challenges arise due to the limited availability of training images and the potentially small number of testing images for each patient, necessitating the development of robust methods. Nevertheless, the results have far-reaching implications for improving cancer diagnosis and treatment outcomes. Additionally, experiments with a set of microscopic images and manual segmentation by a medical expert have shown the effectiveness of these methods. Notably, the proposed method achieves a 100% accuracy rate in correctly classifying poorly differentiated squamous cell carcinoma. As a result, this approach holds promise for automating the separation and classification of squamous cell carcinoma cell nuclei from color microscopic images.

References

[1] X. Xie, J. Niu, X. Liu, Z. Chen, S. Tang, and S. Yu, “A survey on incorporating domain knowledge into deep learning for medical image analysis,” Med. Image Anal., vol. 69, pp. 1–27, 2021, doi: 10.1016/j.media.2021.101985.

[2] B. Wiestler and B. Menze, “Deep learning for medical image analysis: a briefintroduction,” Neuro-Oncology Adv., vol. 2, no. Supplement_4, pp. iv35–iv41, 2020, doi: 10.1093/noajnl/vdaa092.

[3] Willemink, M. J. et al. Preparing medical imaging data for machine learning. Radiology192224 (2020).Arimura H, Soufi M, Kamezawa H, Ninomiya K, Yamada M. Radiomics with artificial intelligence for precision medicine in radiation therapy. J Radiat Res 2019; 60: 150–7. doi: 10.1093/jrr/rry077

[4] Fusco R, Di Marzo M, Sansone C, Sansone M, Petrillo A (2017) Breast DCE-MRI: lesion classification using dynamic and morphological features by means of a multiple classifier system. Eur Radiol Exp 1:10

[5] King AD, Chow KK, Yu KH et al (2013) Head and neck squamous cell carcinoma: diagnostic performance of diffusion-weighted MR imaging for the prediction of treatment response. Radiology 266:531–538

[6] Becker AS, Marcon M, Ghafoor S, Wurnig MC, Frauenfelder T, Boss A (2017) Deep learning in mammography: diagnostic accuracy of a multipurpose image analysis software in the detection of breast cancer. Investig Radiol 52:434–440

[7] Kwan SW, Fidelman N, Ma E, Kerlan RK Jr, Yao FY (2012) Imaging predictors of the response to transarterial chemoembolization in patients with hepatocellular carcinoma: a radiological-pathological correlation. Liver Transpl 18:727–736

[8] Prevedello L. Challenges related to artificial intelligence research in medical imaging and the importance of image analysis competitions. Radiology: Artificial Intelligence 2019

[9] Aerts HJWL, Velazquez ER, Leijenaar RTH, Parmar C, Grossmann P, Carvalho S, et al.. Decoding tumour phenotype by noninvasive imaging using a quantitative radiomics approach. Nat Commun 2014; 5: 4006. doi: 10.1038/ncomms5006