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DESIGN & DEVELOPMENT OF VARIOUS ARTIFICIAL INTELLIGENCE TECHNIQUES IN MEDICAL IMAGE ANALYSIS

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ABSTRACT:
Modern medical imaging systems produce a huge amount of data, which has led medical professionals to look for new ways to handle their data and use the rich information they contain. Medical imaging today has more and more features that come from different kinds of analysis, such as artificial intelligence. Most of the time, these features are used for different kinds of analyses, like deep learning, fuzzy sets, rough sets, uncertain analysis, multi-objective optimisation, swarm intelligence optimisation, and machine learning. Recent changes in electronics have helped research in the field of medical imaging. It uses a number of medical imaging techniques and helps people all over the world in a very important way. Even though high-resolution medical instruments have come a long way, doctors can't always get all the information they need from the outputs of the equipment, and they can't easily use a lot of data without a computer.

Keywords: Medical Imaging, Artificial Intelligence, Optimisation.

INTRODUCTION:

Recent advances in computerized methods for analyzing medical images can help doctors and radiologists with different diagnostic tasks related to assessing and interpreting medical images so that they can make better decisions. In general, the effectiveness of a medical imaging system depends a lot on how accurate and precise the process of diagnosing and assessing diseases is. This depends on how well the image acquisition system works and how well the interpretation system works after that. The use of artificial intelligence (AI) in medical imaging, such as in image processing and interpretation, is one of the most promising areas of health innovation. AI could be used for many things, like getting and processing images, helping with reports, planning follow-ups, storing data, mining data, and many more. AI is likely to have a big effect on a radiologist's daily life because it has so many uses. Everyone agrees that patient data is a very sensitive resource that needs to be kept private and communicated securely. Data protection authorities have rules about how this kind of information can be shared, who owns it, and how it can be used. Aside from legal considerations, organizations and people who are in charge of collecting and sharing this kind of data should also use ethical reasoning to make sure they are making decisions that are morally sound when they share or use these good data resources. Such patient data are an important resource both inside and outside of their natural environment, which is the clinical site. For example, patient data can be used for clinical trials, teaching, research, and training and validating AI solutions. Before using this kind of data in these situations, they must follow the rules about protecting data. Techniques like de-identification, anonymization, and "pseudo-anonymization" can be used to make the data available while protecting the privacy of patients. For example, before medical images leave the clinical center, all personal information that could be used to identify a person is removed. But, as explained later in this document, there are several AI strategies that can be used to train AI models locally (federated learning) or extract key pathological information to make synthetic images (generative adversarial network) without leaving the clinical centers.

According to the local data protection regulation body, de-identification is the process of removing or changing all patient identifiers, such as name, address, and hospital identification number, from the patient data, which is the image metadata in the header. Anonymization gets rid of all the information that can be used to find a patient, so they can't be found. The name, address, and full postcode must be taken out, as well as any other information that, when combined with other information held by or given to the recipient, could be used to identify the patient. Pseudonymisation is a process in which PII is key coded using a unique identifier (i.e. a pseudonym). Such identifiers don't have anything to do with the person, but if needed, a well-protected and separately stored re-identification table could be used to find the person. Artificial intelligence is inherently a field that combines many different areas of study, such as machine learning, computational theory, searching, probability, neurobiology, and so on. It has a lot to do with collecting similar data from a large amount of data, and it can learn from any kind of data, such as numbers, pictures, and videos. Learning about a piece of data can give you the background you need to do research and pull out useful information. The medical industry is having a hard time pre-screening diseases to make people live longer. Prescreening is used in a number of medical situations, such as diagnosing diabetic retinopathy, breast cancer, lung cancer, and brain tumors automatically with an MRI. It is important to choose the right image processing techniques that help machines learn and get information from images. Using techniques from artificial intelligence, you can solve a wide range of big problems quickly and effectively. Image-based modeling needs to use computerized methods for image processing, such as segmentation, registration, and display. Gross tissue type identification has been done successfully with the help of statistical classification techniques and segmentation. Because there isn't much difference between normal and diseased tissue, collecting tissue parameters isn't enough for successful segmentation. Statistical classification may not be able to tell the difference between non-enhancing tumor tissue and normal tissue. Normal anatomical structures have been found with the help of detailed information from a digital atlas about the body.

Medical imaging is an important way to get information about how the body works and how it looks. It is also essential for diagnosing and treating diseases. A lot of clinical tasks that happen every day in health care are based on medical images. As acquisition technology keeps getting better, more and more high-resolution images can be taken that show the structure and function of different parts of the human body in more detail than ever before. Image segmentation, registration, and matching are some of the most important parts of medical image analysis. Medical image analysis has a direct effect on applications like image data fusion, quantitative and time series analysis, biomechanical modeling, making anatomical atlases, visualization, virtual and augmented reality, instrument and patient localization and tracking, etc.

Medical images, for example, are analyzed to find out the exact shape and arrangement of anatomical structures so that a surgeon can plan the best way to reach a target structure before the surgery. Medical images can also be used to look at the connections between structural abnormalities and deformations and certain functional abnormalities and diseases. In radiotherapy, medical image analysis is very important because it lets a lethal dose of radiation be sent to a tumor with as little damage to healthy tissue as possible. In the analysis of digital images, it is hard to separate the object of interest into its parts. Sometimes, fully automatic methods fail, giving wrong results that need to be fixed by a human operator. This is often the case in medical applications, where image segmentation is hard because of limitations in image acquisition, disease, and biological variation. In a 3D scan, each volume element (called a "voxel") or picture element (called a "pixel") is given a name based on the part of the body it belongs to. This helps find the desired areas. In more recent methods, an initial estimate of the structure boundary is given as a curve or surface, and image data is used to fine-tune the initial estimate. A fully segmented scan lets surgeons see the shapes and relative positions of internal structures more clearly and get more accurate measurements of their sizes and distances. Detailed segmentation and the 3D models that come from it can be used to make an anatomical atlas that can be used to teach, show, and train other algorithms. Segmentation is helpful when used on image data from both people with diseases and people who are healthy. People whose scans don't show any pathological abnormalities can be used as a comparison to figure out what's wrong.

LITERATURE REVIEW

Jungo et al. (2021) say that Pymia is an open source Python package for using deep learning to handle and evaluate data in medical image processing. Data handling can be done in 2D, 3D, in full or in patches, and it doesn't matter what deep learning framework is used. Integration into existing deep learning frameworks like TensorFlow and PyTorch. Features like calculating and reporting results (via CSV files or a console) and keeping track of training progress. Deep learning's impact was made stronger by a large number of domain-specific metrics for image segmentation, reconstruction, and regression, as well as by AlexNet, U-net, GPUs, and more data.

Renard et al. (2020) – In this paper, a tool for separating parts of a medical image is used. It is used for clinical diagnosis and surgery with the help of a computer. Deep learning algorithms are better than traditional segmentation in terms of accuracy. The methods for deep learning are complicated. They vary a lot, so it's important that results can be repeated. In this review of the literature, we looked at how the deep learning technique affects the variability and reproducibility of medical images.

Sardanelli et al (2017) Radiologists were the first doctors to use digital technology. They led the way because they were the first doctors to use computer science. They are now probably the most digitally knowledgeable doctors. Even though most people thought that new technologies meant new ways to make images, they also changed a lot about how images are handled, shown, and stored. In fact, the role of radiologists was made more important when new technologies came along. Why should things change now like this.The lesson from the past is that radiologists were open to new technologies that seemed to go beyond radiology, such as non-x-ray modalities like ultrasound and MRI. Radiology has grown to include imaging methods that don't use radiation. It now covers almost all diagnostic medical imaging, as shown by the fact that the word "radiology" is in the titles of many journals. This historical effect happened because radiologists were able to use these methods that didn't use radiation. Also, electronic systems for storing images and reporting on exams were mostly made for radiologists.

Perone et al (2019) Using deep learning algorithms in medical imaging is interesting, but there are many problems that are slowing down progress. Another problem with medical image analysis is that medical images aren't always taken in the same way. Deep learning can't be used for analyzing medical images because they need to be annotated in a lot of detail. Medical data privacy is both a social and a technical problem that needs to be talked about from both points of view. Radiologists need to know how to label medical images. Because of this, it takes time to annotate enough medical data. Semi-supervised learning could be used to take advantage of both the labeled data that already exists and the large amount of unlabeled data. This would solve the problem of "limited labeled data." Another way to deal with the problem of "not enough data" is to create algorithms for "few-shot learning" that use a much smaller amount of data. Even though deep learning technology has worked well, there are many limits and problems in the medical field. DL in the medical field can't be tested well enough to see if it can be used to lower medical costs, improve medical efficiency, and make patients happier. But in clinical trials, it's important to show how well deep learning methods work and come up with rules for how they can be used for medical image analysis.

RESEARCH METHODOLOGY

Most microscopes used in medical imaging are light-optical microscopes that can look at living things between 0.1 m and 1 mm in size. A system of lenses is used to make things bigger. As spatial resolution goes up, photosensitivity goes down. Most of the time, microscopic images are used to find disease in a tissue sample at the level of the cells. Images are sometimes in color and have a good signal-to-noise ratio and good contrast. Images taken with an analysis can be used to count cells, look at the shape of cells, and look at the analysis and distribution of cells.

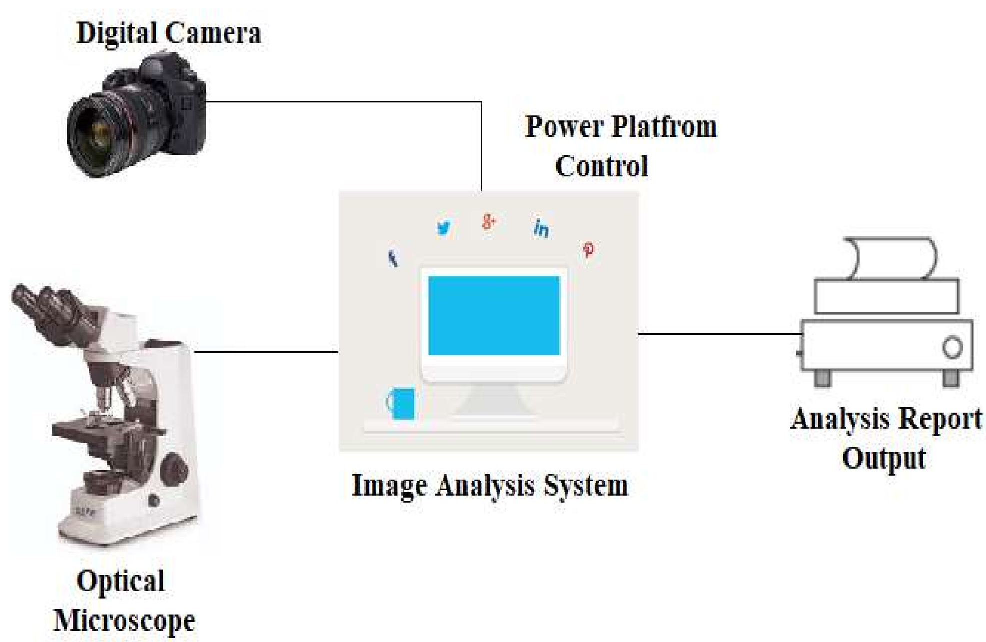

Figure 1 System Architecture

As shown in Figure 1, a digital microscope imaging system combines an optical microscope, digital multimedia, and digital processing technology. Most of the time, this system has three parts:

- The optical module for microscopy.
- The data acquisition module.
- The digital image processing and software control modules.

From these modules, the first optical module can figure out that the microscopic imaging function is being used. The second data acquisition module uses CMOS, CCD, and digital camera devices to take pictures of the images and store them as digital files on the computer's storage devices. The third software control module controls the image capture, processing, and measurement in real time to improve the image quality in the best way. These digital images in real time are watched on computer monitors. After using different Digital Image Processing techniques, Digital Microscopic Imaging systems can capture and show image details more clearly. The imaging technique was chosen because it is known to make pictures that show diagnostically important information. Most of the time, this information is used as part of the domain knowledge to make up for the fact that the property being measured is not easily accessible. Three things must be true for a property that is measured by an imaging device and shown as an image to be useful. It should be able to get into the body without causing too much trouble, and it should be used to ask a medically relevant question.

Features are the contents, properties, or important aspects of an image that can be used to put it in a certain category. Different techniques are used to get features from images in the form of numbers for the same reason. From the extracted features, the model for classifying is made. How well the classifier works and how accurate it is also depend on the features. Most features can be put into three main groups: colour, texture, and shape. Low level features and high level features are two other ways to divide features. Images are used to directly pull out low-level features. Low-level features are used to pull out high-level features. The process of making features from the original image is called "feature extraction."

Object is a thing in the real world, and classification is a way to describe, group, or classify it. Feature detection is a term used in machine vision and image processing. It refers to the steps that are taken to process image data and decide, at each image point, if there is an image feature of a certain type there or not. Feature Extraction is one of the most important parts of Image Analysis. Features are the contents, properties, or important aspects of an image that can be used to put it in a certain category. Different techniques are used to get features from images in the form of numbers for the same reason. From the extracted features, the model for classifying is made. How well the classifier works and how accurate it is also depend on the features.

RESULT ANALYSIS

Experiments are done on 100 MRI images taken from different patients (Jafari-Khouzani et al., 2004) and put together by Jafari-Khouzani et al. It is a Benchmark Dataset that many researchers have used to try out their ideas and see how well they work. The clustered input image's mean, median, and standard deviation are calculated for each color channel or RED, GREEN, and SOM clustering is used, and it uses KNN-based neighbor analysis to gather the same intensity-based pixels and cluster them.

Table 1 Comparison of detection accuracy Proposed Vs. Existing

Approaches	Data Base Image	Existing	Proposed
Abnormal Image	35	31	34
Normal Image	65	62	72
Total Images	100	93	96

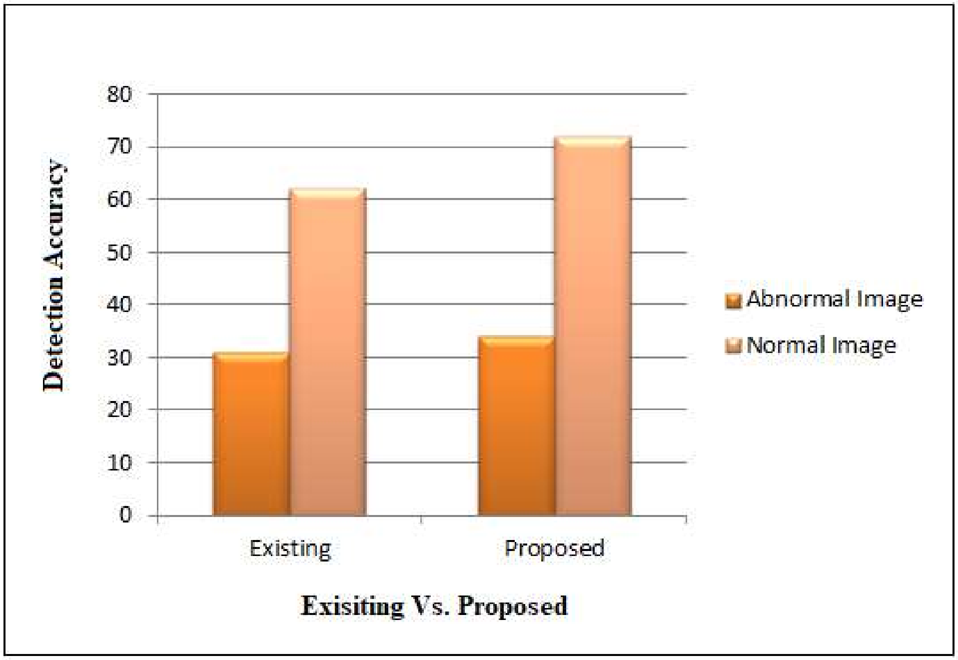

Figure 2. Detection Accuracy

Last, the tumor part is calculated with the help of the winner neurons and separated from the rest of the image using the distance between the pixels' mean, median, and standard deviation. Once the tumor part has been found, the SVM classifier sorts the MRI images into normal or abnormal groups based on their different features, as shown in Table 1 and Figure 2.

Table 2 Comparison of classification accuracy Proposed Vs. Existing

Features	No. of Images	Existing	Proposed
Intensity	13	12	13
Shape	37	27	36

Texture	50	41	49

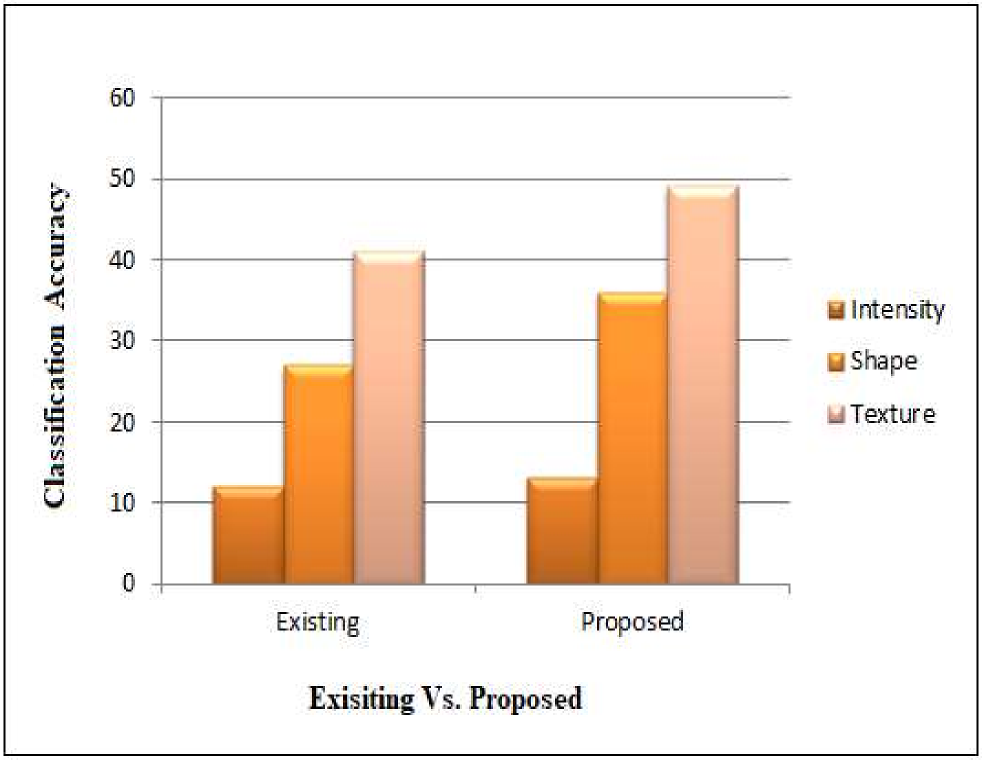

Figure 3. Classification Accuracy

Accuracy Using the failure rate as a guide, the effectiveness or accuracy of the classifiers for each surface dissection method is looked at. The terms "true and false positive" and "real and false negative" could be used to describe this error rate.

CONCLUSION

Noise and data are usually what make up an image's input. To find the target, it needs to be preprocessed first. Image is looked at for initial preprocessing, which should get rid of noise and improve the image so that it can be normalized. The clearer image makes it easier to find useful information. The input image is used to decide whether the image is normal, benign, or malignant. Existing methods follow a few steps to identify, such as looking at the image that was given as input and using a noise removal algorithm that includes competitive, cooperative, and synoptic weight adaptation. Then, the image is improved so that it can be used for further operations. This is done by applying binary operations to the image in order to choose it for future extraction. During preprocessing, noise is taken out of MR images. Here speckle noise removal technique is adapted. Images made with synthetic aperture radar and medical images both have a lot of these speckle noises. Here, noise called "speckle" is taken out of the image before it is looked at.

Image enhancement uses the adaptive histogram equalization method to make the image brighter and increase the level of contrast. It picks the threshold by using different bands. If none of the bands are chosen, a universal threshold is taken into account. In the past, Image Classification with peculiarity selection and extraction has been done, but not very well. The method suggested for the above work includes the steps of image collection, noise removal, brightness enhancement, intensity, shape, and texture feature extraction, feature determination, and feature grouping. In this method, the differences in shape, intensity, and texture are emphasized and used to group things. Using a classifier, the most important tricks are chosen and put in order. So, the proposed system works better than the current system and lives up to expectations. It makes sense that when the data from the MRI and the Image are added to the plan, the results will be more accurate.

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