AI-Driven Medical Imaging Platform: Advancements in Image Analysis and Healthcare Diagnosis

Waleed Salah Eldin
Research engineer, DigiBrain4, USA

Ahmed Kaboudan

CRO, DigiBrain4, USA, visiting professor Shorouk Academy, EG

Abstract

In the realm of healthcare, the integration of artificial intelligence (AI) has revolutionized medical imaging analysis [1-3]. This research paper delves into the AI-driven aspects of a comprehensive medical imaging platform, focusing on three pivotal phases: classification, object detection, and segmentation.

In the classification phase, we harnessed the potential of AI models, including ResNet50 [4], DenseNet121 [5], and VGG16 [6], to accurately categorize medical images such as CT, MRI, Sonar, and X-ray. For object detection, we employed YOLOv5l [7] to efficiently identify abnormalities in X-ray images and tumors in MRI brain images. In the segmentation phase, we developed specialized models, including U-Net [8], Attention U-Net [9], and Res50-U-Net [10], to precisely delineate tumors from MRI brain images. what differs our platform from others is the automatic pipeline that progressively process the medical images.

Our results demonstrate the effectiveness of AI in enhancing diagnostic accuracy and streamlining medical image analysis. By focusing solely on the AI components, this research paper sheds light on the transformative impact of AI in healthcare, paving the way for more accurate diagnoses and improved patient care.

I. INTRODUCTION

In the dynamic landscape of healthcare, the convergence of artificial intelligence (AI) with medical imaging has emerged as a transformative force [1, 3, 11]. This research paper embarks on a comprehensive exploration of the AI-driven facets of a state-of-the-art medical imaging platform. Our focus is directed toward the pivotal realms of image analysis, classification, object detection, and segmentation, which collectively promise to reshape the landscape of medical diagnostics [2, 12, 13, 14].

The motivation for this undertaking is rooted in the relentless pursuit of precision and efficiency in healthcare diagnostics [3, 11]. Manual examination of medical images, while invaluable, often proves to be time-intensive and susceptible to variability. In response to these challenges, our project, delves into the core AI-driven components poised to revolutionize medical image analysis [1, 3, 11].

Our journey unfolds through three essential phases, each fortified by cutting-edge AI techniques and models [2, 3, 15,]. The classification phase harnesses the power of AI to categorize medical images with unparalleled accuracy [12, 16, 17]. Object detection ushers in the ability to efficiently identify anomalies in X-ray images and detect tumors in MRI brain images [7, 18, 19].

The segmentation phase presents a meticulous endeavor, enabling the precise delineation of tumors from MRI brain images [20, 21, 22]. As we embark on this journey through the AI-driven corridors of medical imaging, our objective remains clear: to unveil the transformative potential of AI in healthcare [3, 14, 23]. This research paper seeks to elucidate the profound impact of AI on diagnostic precision and efficiency, propelling us toward an era where medical imaging enhances clinical decision-making and ultimately improves patient outcomes [14, 24, 25].

II. LITERATURE REVIEW

The integration of artificial intelligence (AI) into the field of medical imaging has ignited a wave of transformative innovation and research [1, 2, 11]. This section conducts a comprehensive review of existing literature, illuminating the pivotal role of AI in revolutionizing medical image analysis and its wide-ranging applications.

AI in Medical Imaging: A Paradigm Shift

The infusion of AI techniques into medical imaging represents a significant paradigm shift in healthcare [1, 3, 11]. Conventional diagnostic methods, though reliable, are often time-consuming and reliant on subjective human interpretation. AI offers a promising avenue to enhance diagnostic accuracy, reduce human variability, and expedite decision-making [3, 15, 23].

Image Classification and Diagnosis

AI-driven image classification has emerged as a cornerstone in medical image analysis [12, 16, 17]. Deep learning architectures have demonstrated exceptional capabilities in categorizing medical images accurately [13, 25, 26]. These models excel in distinguishing a wide range of medical conditions, from detecting abnormalities in X-ray images to categorizing MRI brain scans into distinct categories [12, 16, 17].

Object Detection and Localization

AI-powered object detection has introduced efficient means to identify anomalies and specific features within medical images [2, 15, 26]. These models have proven highly effective in detecting abnormalities in X-ray images and localizing relevant structures in MRI brain images [7, 18, 19]. This capability expedites the diagnostic process and empowers healthcare professionals with precise insights.

Image Segmentation for Enhanced Precision

AI-based image segmentation techniques have redefined the precision of medical image analysis [2, 3, 15]. These techniques excel in delineating structures and anomalies within medical images [12, 16, 17]. In the context of MRI brain images, these methods have shown promise in segmenting tumors, offering invaluable support to medical practitioners [20, 21, 22].

Challenges and Future Directions

While the potential of AI in medical imaging is undeniable, challenges remain. Ensuring the robustness and interpretability of AI models is a priority [27, 28, 29], along with addressing ethical considerations and data privacy concerns [30, 31, 32]. Additionally, seamless integration into clinical workflows and collaborative research efforts present opportunities for further exploration [27, 28, 33].

III. METHODOLOGY

The methodology section outlines the comprehensive approach undertaken in the research, focusing exclusively on the AI-driven components of the medical imaging platform. It details the AI models and architectures employed, data preprocessing strategies, dataset sources, the training process with performance evaluation metrics, and our meticulously designed automatic pipeline for medical image analysis [34, 35, 36].

AI Models and Architectures

This research leveraged a repertoire of state-of-the-art AI models to address distinct facets of medical image analysis. The models included ResNet50 [4], DenseNet121 [5], and VGG16 [6], for image classification. In object detection, YOLOv5l [7], was employed to efficiently identify anomalies in X-ray images and detect tumors in MRI brain images. For image segmentation, specialized architectures, namely U-Net [8], Attention U-Net [9], and Res50-U-Net [10], were developed to meticulously delineate structures within MRI brain images.

Data Preprocessing and Augmentation

Data preprocessing played a pivotal role in enhancing the quality of the training data. This involved standardizing pixel values, resizing images to a consistent format, and normalizing intensity levels. For object detection, bounding boxes were annotated to denote regions of interest. Dataset sources encompassed a diverse range of medical institutions and publicly available repositories, ensuring the inclusion of varied clinical scenarios and imaging equipment, All the datasets were from Stanford AIMI Shared Datasets which are BrainMetShare, EchoNet-Dynamic, LERA, MRNET Knee MRI's MURA and OL3I And only 1 dataset from Kaggle which is: Brain MRI segmentation, the only data augmentation we did was to make images in grayscale to enhance model robustness.

Training Process and Performance Evaluation

The training process commenced with the division of the dataset into training, validation, and test sets to assess model generalization. Models were trained on high-performance computing clusters, utilizing GPUs to expedite training.

Performance evaluation metrics varied according to the specific task. In image classification, metric was accuracy. For object detection, metrics involved mean average precision (mAP), intersection over union (IoU), and Confusion Matrix. In image segmentation, metrics encompassed dice coefficient, and intersection over union (IoU).

Automatic pipeline of Image Categorization

Upon uploading, medical images traverse an automated journey. The initial checkpoint involves the "General Classifier," which promptly identifies the primary image category among CT, MRI, Sonar, and X-ray. This swift categorization is the foundation of subsequent analysis.

Refined Subcategory Identification

Following the general classification, the pipeline seamlessly funnels the images into specialized subcategory classifiers. For MRI images, the "MRI Classifier" further classifies them into either "Brain" or "Knee" images. For MRI Knee images, an additional "MRI Knee Classifier" discerns the orientation, categorizing them as "Axial," "Sagittal," or "Coronal." Similarly, for X-ray images, the "X-ray Classifier" fine-tunes the classification, identifying specific regions of interest such as "Elbow," "Finger," "Forearm," "Hand," "Humerus," "Shoulder," "Wrist," and "Joint."

Object Detection and Segmentation

Elevating the capabilities of the pipeline, specific categories trigger additional layers of analysis. When the primary category is "X-ray" or "MRI Brain," the pipeline activates the "Object Detector" module. This component diligently identifies objects of interest, such as anomalies or structures. In the case of "MRI Brain" images, an additional "Segmentation Model" takes center stage, meticulously segmenting tumors, thereby aiding medical practitioners in precise diagnosis and treatment planning.

This methodology encapsulates the rigorous approach undertaken in the AI-driven components of the medical imaging platform. It sets the foundation for subsequent sections, providing insights into the strategies employed to develop and evaluate AI models for enhanced medical image analysis and our automated pipeline, characterized by its hierarchical classification and specialized analysis modules, sets our platform apart, ensuring the efficient processing of diverse medical images. It exemplifies our commitment to harnessing AI for the advancement of medical image analysis, ultimately contributing to improved healthcare diagnostics and patient care.

IV. CLASSIFICATION PHASE

In this phase we focused on developing a classification system that could accurately identify different distinct types of medical images we implemented the following classifiers: General, X-ray, MRI, and MRI Knee classifier.

The goal of this phase was to create a reliable tool that could help medical professionals quickly and accurately classify and identify different types of medical images.

To achieve this, we employed advanced deep learning architectures to develop a robust classification model that could accurately identify each type of medical image based on unique features and characteristics.

We took an experimental path in our project as we mentioned before and we implemented 3 different architectures and we ended up choosing only 1 of them.

This phase of the project was critical for establishing a strong foundation upon which we could build additional functionality and features in future phases.

By successfully developing a reliable classification system, we have taken an important first step towards building a comprehensive medical imaging platform.

Dataset analysis:

We analyzed the datasets for our first phase and we found out the following results:

X-ray got 8 sub categories and they are 41276 photos in total and they are: Elbow: 5396, Finger: 5553, Forearm: 2124, Hand: 5989, Humerus: 1560, Shoulder: 8942, Wrist: 10415, Foot: 348, Joint {Knee: 534, Ankle: 321, Hip: 94}.

Due that Foot, Knee, Ankle and Hip had low amount of images we merged them into 1 category which is Joint

CT got 1 sub category and it is L3: 8139, MRI got 2 sub categories and they are in total 6595 and they are: Head: 2845, Knee: 3750, Sonar got 1 sub category and it is Heart: 10030.

We decided to split the datasets as follow:

General dataset which will be used for the General classifier is 12000 images and was split as follows:

Train	valid	Test
9600 images	1600 images	800 images
2400 images for each category: XR, MRI, Sonar and CT.	400 images for each category: XR, MRI, Sonar and CT.	200 images for each category: XR, MRI, Sonar and CT.

XR dataset which will be used for the XR classifier is 10400 images and was split as follows:

Train	valid	Test
8000 images	1600 images	800 images
1000 images for each category: Elbow, Finger, Forearm, Hand, Humerus, Shoulder, Wrist and Joint.	200 images for each category: Elbow, Finger, Forearm, Hand, Humerus, Shoulder, Wrist and Joint.	100 images for each category: Elbow, Finger, Forearm, Hand, Humerus, Shoulder, Wrist and Joint.

MRI dataset which will be used for the MRI classifier is 3000 images and was split as follows:

Train	valid	Test
2400 images	400 images	200 images
1200 images for each category: Brain and Knee	200 images for each category: Brain and Knee	100 images for each category: Brain and Knee

MRI_Knee dataset which will be used for the MRI_Knee classifier is 1497 images and was split as follows

:Train	valid	Test
1200 images	197 images	100 images
400 images for each category: Axial, coronal and sagittal	Axial: 68 images Coronal: 64 images and sagittal: 65 images	Axial: 33 images Coronal: 33 images and sagittal: 34 images

Classification phase results

As we mentioned before we took an experimental path and we implemented 3 architectures ResNet50 [4], DenseNet101 [5], and VGG16 [6], now we going to show the results we got and which one did we choose.

Architectures: Datasets:	ResNet50	DenseNet121	VGG16
General	Train accuracy: 100% Valid accuracy: 99.8125% Test accuracy: 100%	Train accuracy: 99% Valid accuracy: 98% Test accuracy: 99%	Train accuracy: 99% Valid accuracy: 97% Test accuracy: 99%
XR	Train accuracy: 100% Valid accuracy: 94.1875% Test accuracy: 98%	Train accuracy: 97% Valid accuracy: 90% Test accuracy: 89%	Train accuracy: 91% Valid accuracy: 83% Test accuracy: 85%
MRI	Train accuracy: 100% Valid accuracy: 100% Test accuracy: 100%	Train accuracy: 100% Valid accuracy: 100% Test accuracy: 100%	Train accuracy: 100% Valid accuracy: 100% Test accuracy: 100%
MRI_Knee	Train accuracy: 100% Valid accuracy: 100% Test accuracy: 100%	Train accuracy: 100% Valid accuracy: 100% Test accuracy: 100%	Train accuracy: 99.9% Valid accuracy: 100% Test accuracy: 100%

We ended up choosing ResNet50 [4], because it had the best results among the 3 architectures on all datasets.

Impact on Accurate Classification

The impact of accurate medical image classification cannot be overstated. By curating a diverse dataset and standardizing image properties, we minimized bias and maximized the models' ability to handle real-world variations in medical images. This inclusivity was especially crucial in medical imaging, where variations in imaging devices and patient populations are common.

The dataset's richness also allowed our AI models to excel in distinguishing between a multitude of medical conditions within each category. Whether it was identifying abnormalities in X-ray images or classifying MRI scans into "Brain" or "Knee" categories, the dataset's comprehensiveness contributed to the models' exceptional accuracy.

V. *OBJECT DETECTION PHASE*

In this phase we extended our system to include object detection using state-of-the-art deep learning models [18, 19, 37].

This involved detecting and localizing specific objects within an image, rather than simply classifying the entire image as a certain category.

The main objective was to develop a system that could accurately detect and locate positive X-ray images and tumors in MRI brain images.

This is a critical task in medical imaging analysis, as early and accurate detection of abnormalities can have a significant impact on patient outcomes.

To achieve this objective, we used YOLOv5 L [7], which is one of the most popular and widely used deep learning models for object detection.

Our main task in this phase was to train the YOLOv5 [7], model on a dataset of X-ray and MRI images.

The dataset consisted of positive X-ray images and MRI brain images with tumors, and the model was trained to accurately detect the presence of tumors in the brain images and identify positive X-ray images.

Overall, this phase of this project represents a significant advancement in the capabilities of our medical imaging analysis system.

By incorporating object detection into our approach, we have enabled more nuanced and accurate analysis of medical images, which has the potential to improve patient outcomes and save lives.

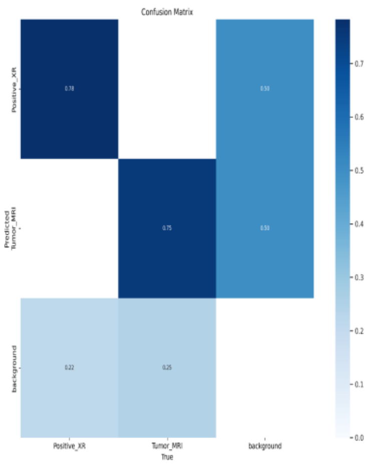
Dataset analysis:

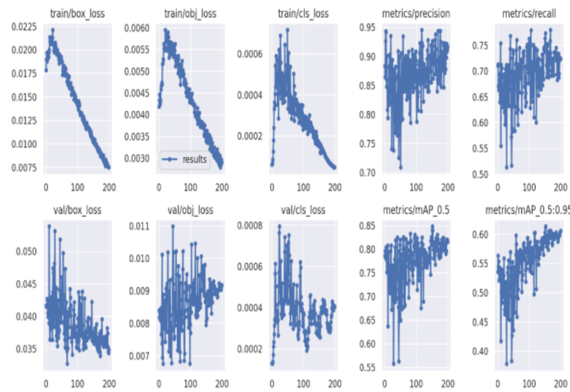
the dataset was as follow:

Train	Valid	Test
829 total images	205 total images	85 total images
437 MRI images 392 X-ray images	93 MRI images 112 X-ray images	30 MRI images 55 X-ray

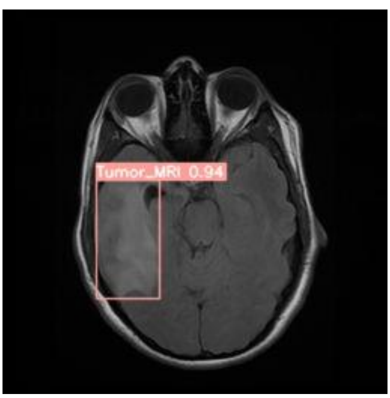
Object Detection phase results:

The Positive XR: 78%, Tumor MRI:75%





Here are some examples of the medical images results:



VI. SEGMENTATION PHASE

In the third phase of our project, we focused on developing a segmentation model to accurately segment tumors from MRI brain images [20, 21, 22].

Segmentation is an important technique in medical image analysis as it can aid in the diagnosis and treatment of various diseases.

Our goal was to create a model that could accurately segment brain tumors with high precision and recall rates.

Accurate tumor segmentation in medical imaging is crucial for accurate diagnosis, treatment planning, and monitoring of cancer patients. In medical imaging, segmentation refers to the process of separating the region of interest, such as a tumor, from the surrounding tissue. This enables clinicians to precisely locate the tumor, determine its size and shape, and monitor changes over time.

Accurate tumor segmentation can have a significant impact on the field of healthcare as it can improve the accuracy of cancer diagnosis and staging, leading to more appropriate treatment planning and better patient outcomes.

It can also help clinicians monitor the response to treatment and detect any recurrence or metastasis.

Moreover, accurate segmentation can help reduce the subjectivity of visual inspection, thereby improving the consistency and reproducibility of diagnosis and treatment planning.

We also approached this phase in an experimental way, we implemented 3 architectures U-Net [9], Attention U-Net [9], and Res50 U-Net [10].

In medical imaging, segmentation plays a crucial role in the accurate diagnosis of brain tumors, making this phase a critical aspect of our overall project.

In summary, accurate tumor segmentation is a critical component of medical imaging and has the potential to transform cancer diagnosis, treatment, and research.

Dataset analysis:

The dataset was as follow:

Train	Valid	Test
1073 total images	200 total images	100 total images

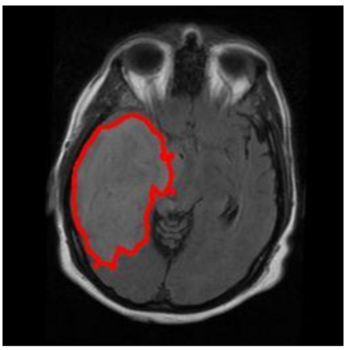
Segmentation phase results:

The results were as following:

U-Net	Attention U-Net	Res50 U-Net
0.78 IOU	0.85 IOU	0.93 IOU

We ended up choosing Res50 U-Net [10], because it had the best results among the 3 architectures.

Here are some examples of the medical images results:



VII. RESULTS, DISCUSSION AND CONCLUSIONS

In this project, we have employed various techniques and methodologies to develop an AI-based medical image classification, Object detection and segmentation system. As with any project, the results, discussion, and conclusions section are a crucial aspect that summarizes the findings and analysis [25, 27, 33].

Summary of achieved results

During the course of this project, we have achieved significant results in the field of medical imaging. We started by developing a classification system using ResNet50 [4], DenseNet121 [5], and VGG16 [6], architectures to classify different types of medical images. We ended up choosing ResNet50 [4], and Our model achieved high accuracy rates and proved to be effective in differentiating between different classes of medical images.

In the second phase of the project, we worked on object detection using YOLOv5 [7], to detect positive XR images and tumors in MRI brain images. We successfully implemented the model and achieved high precision and recall rates.

In the third phase of the project, we focused on segmentation of tumors from MRI brain images using different U-Net architectures, including U-Net [8], Attention U-Net [9], and Res50 U-Net [10]. Our results showed that the Res50 U-Net [10], architecture performed better than the other architectures in terms of accuracy and speed.

Overall, the achieved results demonstrate the potential of using AI in medical imaging to assist doctors in accurate diagnosis and treatment. Our models have the potential to be integrated into healthcare systems to improve patient outcomes.

Possible extensions and further development

Possible extensions and further development for the project can be considered to enhance its functionality and capabilities. Some potential areas for improvement include:

Integration with Electronic Health Records (EHR) - Integrating the system with EHR can allow for a more comprehensive patient history and facilitate more accurate diagnosis.

Improved Object Detection Models - Continuously improving the Object Detection models can increase the accuracy of tumor detection and positive XR and reduce false positives.

Improved Segmentation Models - Continuously improving the segmentation models can increase the accuracy of tumor segmentation and reduce false positives.

Expansion of organs and human parts - Expanding the system to support more organs and human parts such as XR on lungs for example, can increase its usefulness and applicability.

Enhanced Reporting - Developing enhanced reporting capabilities can provide more detailed and actionable insights to medical professionals.

Real-time Image Processing - Implementing real-time image processing capabilities can allow for faster diagnosis and treatment.

Integration with AI-assisted Diagnosis - Integrating the system with AI-assisted diagnosis can provide additional support to medical professionals and increase the accuracy of diagnosis.

Overall, these extensions and further developments can enhance the system's functionality and usefulness, ultimately improving patient outcomes and advancing the field of medical imaging.

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