Intracranial Tumor Detector

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Declaration and Acknowledgment

We declare that:

- This project is our original work.
- This project is not a reproduction of any other published or exhibited work from another source, local or international.
- The results presented here were obtained from experiments, research, or experiments we conducted ourselves.
- This is the first time that these results have been presented to the exhibition of JoYS, and the research has not been previously shared among any other competitions to be judged.

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List of Abbreviations

Abbreviation	**Definition**
MEs	Medical Errors
ICTD	Intracranial Tumor Detector
AI	Artificial Intelligence
DL	Deep Learning
CNN	Convolutional Neural Network
MRI Magnetic	Resonance Imaging
GUI Graphical	User Interface
WHO	World Health Organization
MR	Magnetic Resonance

Abstract

Medical errors (MEs) represent one of the most critical challenges within the healthcare sector, and they can be categorized into several types, this project focuses on diagnostic errors. Misdiagnosis is one of the most common types of malpractice, with cancer being one of the most likely conditions to be misdiagnosed. Given the malignant and unpredictable nature of cancer, diagnostic errors could result in irreversible life-threatening complications or even mortality [1].

The Intracranial Tumor Detector (ICTD) implements the revolutionary technology of Artificial Intelligence (AI) within Deep Learning (DL) and Convolutional Neural Networks (CNN) in image classification to ensure no tumors go undetected. First, we built an MRI (Magnetic Resonance Imaging) dataset, compromising a public dataset from Kaggle [2] and images from a local hospital. We preprocessed the images by resizing, normalizing, and augmenting them. After that, we ran them through a Neural Network that extracts and learns features from them, then classifies them into two groups; brain tumor, and no tumor. Then we created a Graphical User Interface (GUI) for medical professionals.

Finally, we analyzed the results and calculated accuracy improvement over time, an accuracy of over **65%** was achieved. We concluded that higher accuracy could have been achieved if better processing power had been available and better algorithms and tools had been used. Nevertheless, this concept is applicable and crucial for saving lives.

Keywords

Brain Tumors, MRI, Misdiagnosis, Medical Errors, AI, CNN, DL.

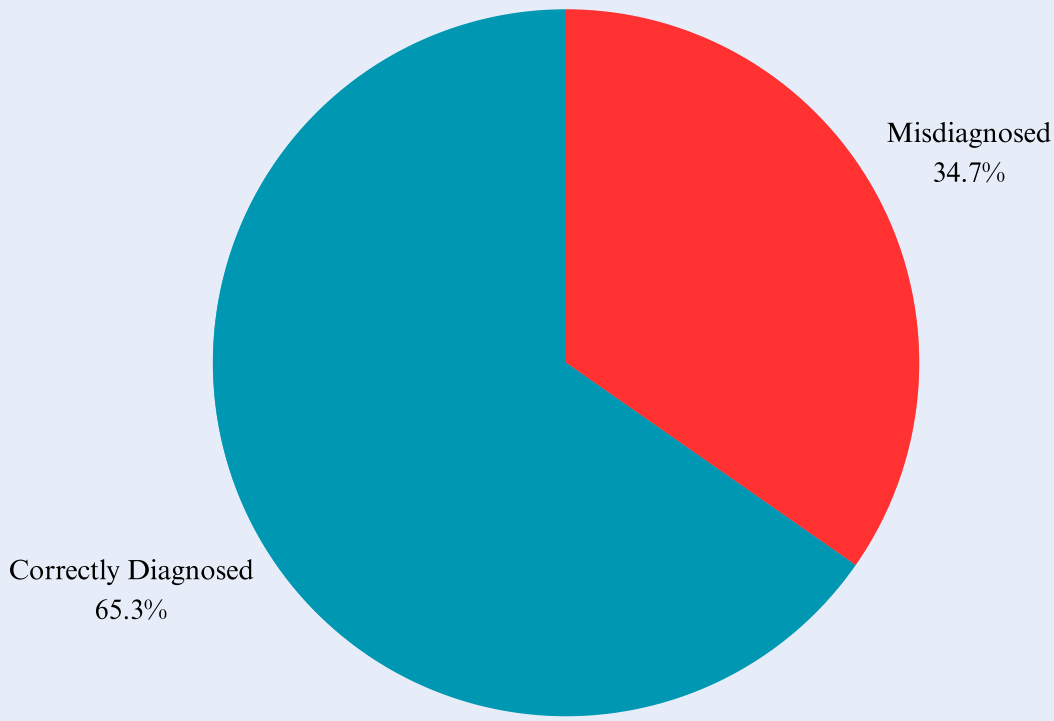
Introduction

Problem Statement

In a report by the World Health Organization (WHO), it is shown that **0.3%** of patients receiving healthcare die due to preventable MEs. Moreover, MEs occur in **10%** of worldwide hospitalizations annually [3]. More importantly, the rate of errors in radiology is **3-5%**; these numbers are alarming and emphasize the importance of a solution [4]. Furthermore, a report published by Medscape showed that approximately **42%** of radiologists have faced lawsuits for misdiagnosis. Additionally, several researchers concluded that there is a relationship between workloads and diagnostic errors, and frequently the diagnostic errors are grave [5] [6].

To better understand the problem, we conducted a questionnaire among medical professionals and students, revealing that **35%** of beneficiaries of the Jordanian health sector have suffered misdiagnosis. Moreover, the questionnaire showed that approximately **15%** of Jordanians wait more than one month to get an MR (Magnetic Resonance) image, **10%** of whom wait more than three months. This highlights another problem, which is the delay in getting imaged. In the case of brain cancer, such delay could lead to the progression into more advanced stages and a decrease in survival rate.

Incidence of Radiology Misdiagnosis in Jordan



Brain tumors

Brain tumors can be defined as the abnormal growth of cells in the brain or nearby tissue (e.g., meninges, pituitary gland, pineal gland, nerves, and blood vessels). Generally, tumors can be classified into benign (Non-Cancerous) and malignant (Cancerous). However, tumors can be classified based on a broad set of criteria (e.g., stages, grades, etc.) as displayed in the figures below [7].

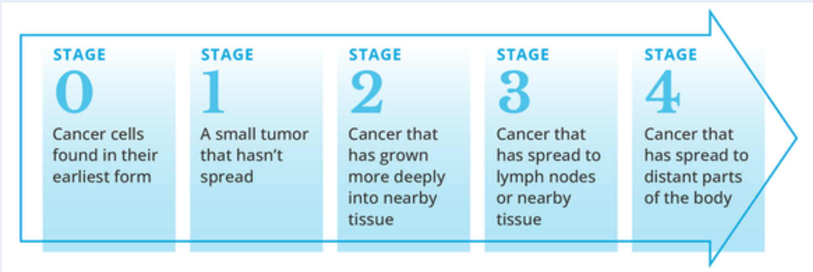


Figure 1

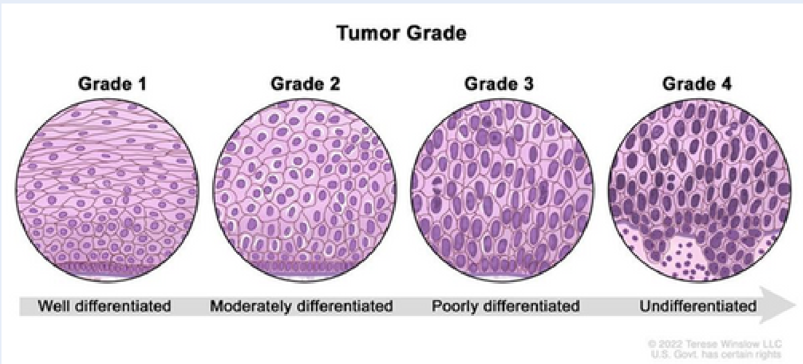


Figure 2

Literature Review

Several studies on the implementation of AI in detecting brain tumors have been published. For example, in 2023, a review of advances in the use of AI in brain tumor diagnosis showed that between 2010 and 2022, twenty-five studies had been published on this subject [8]. Additionally, a paper published in 2022 states that they were able to build a model for image classification [9]. Furthermore, a study published in 2023 discussed a brain tumor segmentation model [10]. However, despite existing models, no operational models are employed in healthcare centers. Moreover, this field still lacks proper research and funding in Jordan.

Hypothesis

In order to solve this problem, we proposed a hypothesis consisting of 4 steps, as displayed below:

Database Collection
Gathering both publicly available MRI images from Kaggle and hospital-sourced images.

Image Preprocessing
Resizing, normalizing, and augmenting the images to allow better feature extraction

Building and Training the Model
Utilizing TensorFlow and other DL tools for object detection and image classification

Creating a GUI for Healthcare Providers We used python, CSS, HTML, and other languages to make a simple and practical user interface

Methodology

Database Collection

Our dataset is divided into training and testing datasets. The training dataset consists of **2870** images from Kaggle [2], pre-classified into 4 smaller datasets: glioma, meningioma, pituitary tumors, and no tumor. Additionally, it includes Magnetic Resonance (MR) images of **20** patients obtained from a local hospital. On the other hand, the testing dataset comprises **370** MR images.

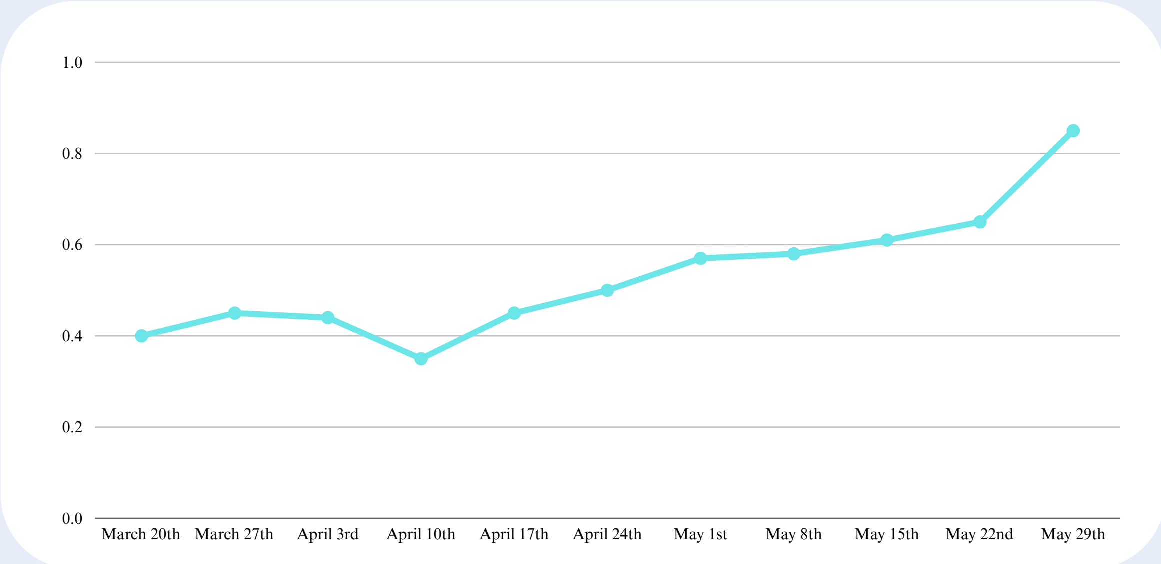
Building and Training the Model

After building the dataset, we used Python to resize the images to a size of **256*256** pixels. We then normalized the pixel values to a range from 0 to 1. Next, we augmented the images by rotating them vertically and horizontally to increase diversity. Image preprocessing was necessary for enhancing accuracy and minimizing error.

Deep learning (DL) was used for object detection and image classification. MR images were classified based on pixel values into tumor and no tumor classes. A convolutional neural network (CNN) implemented via TensorFlow was the key DL algorithm used in our model. The CNN has nine layers: one input, one output, and seven hidden layers. When an MR image is input into the CNN, the input layer processes the pixels and passes the data through the network. The hidden layers, which include convolutional and pooling layers, extract and learn features from the images using certain algorithms. If a threshold value is reached, the output layer assigns the image a probability between 0 and 1. If the value is less than 0.5, the image is labeled as a Brain Tumor; if it is greater than 0.5, it is labeled as No Tumor.

Results

After training the model, we tested it on the testing dataset and analyzed the accuracy over time. After various optimizations and refinements, the model yielded an accuracy exceeding **85%**. This result highlights the need for further development to enhance the model's performance.



Additionally, we tested the model on images of 5 patients from a local hospital. The results are displayed in the table below:

Patient ID	Patient 1	Patient 2	Patient 3	Patient 4	Patient 5
Patient Age/Gender	**59/F**	**29/F**	**76/F**	**17/F**	**25/F**
Tumor Presence	Not Present	Not Present	Not Present	Not Present	Not Present
Prediction	No Tumor	No Tumor	No Tumor	No Tumor	No Tumor

Conclusion and Recommendations

Our findings led us to believe that higher accuracy could have been achieved with better processing capabilities and additional tools (e.g., AutoML and Google Cloud). We recommend further development of this model and future models by embedding features that can segment, highlight, and measure the dimensions of brain tumors. Additionally, integrating spectroscopy, which can help distinguish tumor type and aggressiveness based on the presence and concentration of certain metabolites within the neoplasm, can significantly enhance the model.

On a broader scale, a comprehensive system that saves data, records patient history, provides diagnoses, and offers treatment plans could revolutionize the medical field, saving lives, costs, and time. We also emphasize the importance of funding and research in this area due to its great potential. However, respecting medical ethics, such as patient privacy, is crucial.

Tools and Materials

References

1. Bieber, C. (2024). Medical Malpractice Statistics of 2024. Forbes. https://www.forbes.com/advisor/legal/personal-injury/medical-malpractice-statistics/

2. Kumar, J. (2021). Brain Tumor MRI Classification: TensorFlow CNN. Kaggle. https://www.kaggle.com/code/jaykumar1607/brain-tumor-mri-classification-tensorflowcnn/input

3. Ta'an, W. A. F., Suliman, M. M., Al-Hammouri, M. M., & Ta'an, A. (2021, April). Prevalence of medical errors and barriers to report among nurses and nursing students in Jordan: a cross-sectional study. In Nursing Forum (Vol. 56, No. 2, pp. 284-290).

4. Brady A. P. (2017). Error and discrepancy in radiology: inevitable or avoidable?. Insights into imaging, 8(1), 171–182. https://doi.org/10.1007/s13244-016-0534-1

5. Gray Ritter Graham. (2023). Diagnostic Errors Involving MRI and CT scans. St. Louis, MO: Gray Ritter Graham. https://www.grgpc.com/gray-ritter-graham-blog/diagnostic-errorsinvolving-mri-and-ct-scans

6. Kasalak, Ö., Alnahwi, H., Toxopeus, R., Pennings, J. P., Yakar, D., & Kwee, T. C. (2023). Work overload and diagnostic errors in radiology. European journal of radiology, 167, 111032. https://doi.org/10.1016/j.ejrad.2023.111032

7. Johns Hopkins Medicine. (n.d.). Brain tumor. Johns Hopkins Medicine. Retrieved May 27, 2024, from https://www.hopkinsmedicine.org/health/conditions-and-diseases/brain-tumor

8. Kaifi, R. (2023). A review of recent advances in brain tumor diagnosis based on ai-based classification. Diagnostics, 13(18), 3007.

9. Khan, A. H., Abbas, S., Khan, M. A., Farooq, U., Khan, W. A., Siddiqui, S. Y., & Ahmad, A. (2022). Intelligent model for brain tumor identification using deep learning. Applied Computational Intelligence and Soft Computing, 2022, 1-10.

10. Ottom, M. A., Abdul Rahman, H., Alazzam, I. M., & Dinov, I. D. (2023). Multimodal Stereotactic Brain Tumor Segmentation Using 3D-Znet. Bioengineering, 10(5), 581.