BMS INSTITUTE OF TECHNOLOGY & MANAGEMENT
(Autonomous Institute Affiliated to VTU)
YELAHANKA, BENGALURU - 560064

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

PROJECT BASED LEARNING

Even Semester - 2022-23

Report of

"Image segmentation for medical diagnosis using deep learning"

Design and Analysis of Algorithm – 21CS46

Software Engineering – 21CS47

IV Semester

IV – 'B'

Submitted By

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2022-2023

INSTITUTE VISION

To emerge as one of the finest technical institutions of higher learning, to develop engineering professionals who are technically competent, ethical and environment friendly for betterment of the society.

INSTITUTE MISSION

Accomplish stimulating learning environment through high quality academic instruction, innovation and industry-institute interface.

DEPARTMENT VISION

To develop technical professionals acquainted with recent trends and technologies of computer science to serve as valuable resource for the nation/society.

DEPARTMENT MISSION

Facilitating and exposing the students to various learning opportunities through dedicated academic teaching, guidance and monitoring.

PROGRAM EDUCATIONAL OBJECTIVES

1. Lead a successful career by designing, analyzing and solving various problems in the field of Computer Science & Engineering.
2. Pursue higher studies for enduring edification.
3. Exhibit professional and team building attitude along with effective communication.
4. Identify and provide solutions for sustainable environmental development.

Program Specific Outcomes (PSOs):

1. Analyze the problem and identify computing requirements appropriate to its solution.
2. Apply design and development principles in the construction of software systems of varying complexity.

Design and Analysis of Algorithm – 21CS46 - Course Outcomes (COs) w.r.t this PBL	
CO	The students will be able to:
CO 1:	Discuss computational solution to well-known problems like searching, sorting etc.
CO 2:	Apply different algorithmic technique for problem solving.
CO 3:	Analyze the asymptotic performance of algorithms.
CO 4:	Design and implement applications using suitable algorithmic techniques.

Software Engineering – 21CS47 - Course Outcomes (COs) w.r.t this PBL	
CO	The students will be able to:
CO 1:	Apply the principles, concepts, methods, and techniques of the Software Engineering.
CO 2:	Use the techniques, skills and modern engineering tools necessary for engineering practice.
CO 3:	Analyze the components and process of a given scenario pertaining to it's realistic constraints.

Project to Program Outcomes (PO) Mapping

Project Name: Image segmentation for medical diagnosis using deep learning

COURSE	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12
DAA (21CS46)	√	√	√	√	√	√	√	√	√	√	√	√

COURSE	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12
SE (21CS47)	√	√	√		√			√	√	√		√

Program outcomes (POs):	
PO1	**Engineering knowledge:** Apply the knowledge of Mathematics, Science, Engineering fundamentals and an engineering specialization to the solution of complex engineering problems
PO2	**Problem analysis:** Identify, formulate, review research literature, and analyse complex Engineering problems reaching substantiated conclusions using first principles of mathematics, Natural sciences and engineering sciences
PO3	**Design/development of solutions:** Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

PO4	**Conduct investigations of complex problems**: Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the Information to provide valid conclusions
PO5	**Modern tool usage**: Create, select, and apply appropriate techniques, resources, and modern Engineering and IT tools including prediction and modelling to complex engineering activities with an understanding of the limitations.
PO6	**The engineer and society:** Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.
PO7	**Environment and sustainability:** Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for Sustainable development
PO8	**Ethics:** Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.
PO9	**Individual and team work:** Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings
PO10	**Communication:** Communicate effectively on complex engineering activities with the engineering Community and with society at large, such as, being able to comprehend and write effective reports And design documentation, make effective presentations, and give and receive clear instructions.
PO11	**Project management and finance:** Demonstrate knowledge and understanding of the Engineering and management principles and apply these to one’s own work, as a member and Leader in a team, to manage projects and in multidisciplinary environments.
PO12	**Life-long learning:** Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

Project to Program Specific Outcomes (PSO) Mapping

Program Specific Outcomes (PSOs):	
PSO1	Analyze the problem and identify computing requirements appropriate to its solution.
PSO2	Apply design and development principles in the construction of software systems of varying complexity.

Project Name: Image segmentation for medical diagnosis using deep learning

COURSE	PSO1	PSO2
DAA – 21CS46	√	√
SE – 21CS47	√	√

Abstract:

This project focuses on semantic image segmentation for medical images, including X-rays, CT scans, MRIs, and more, employing deep learning techniques, with a particular emphasis on Convolutional Neural Networks (CNNs) and the U-Net architecture. The project's core objective is to harness the power of CNNs, specifically the U-Net model, to automate the precise identification and categorization of anatomical structures and anomalies within medical images.

Design and Analysis of algorithms play a pivotal role in this project. The process begins with comprehensive data collection and preprocessing to ensure high-quality input. The U-Net architecture is then tailored and optimized, considering the complexities and intricacies of medical images. Extensive training, validation, and fine-tuning are performed, with algorithmic design decisions aimed at minimizing error and enhancing segmentation accuracy.

The project also explores advanced techniques such as data augmentation, regularization, and model optimization to improve the algorithm's robustness and efficiency. Ultimately, this endeavour seeks to develop a reliable, automated tool capable of streamlining the medical image analysis process, reducing human error, and increasing the accuracy and confidence of diagnoses in clinical settings.

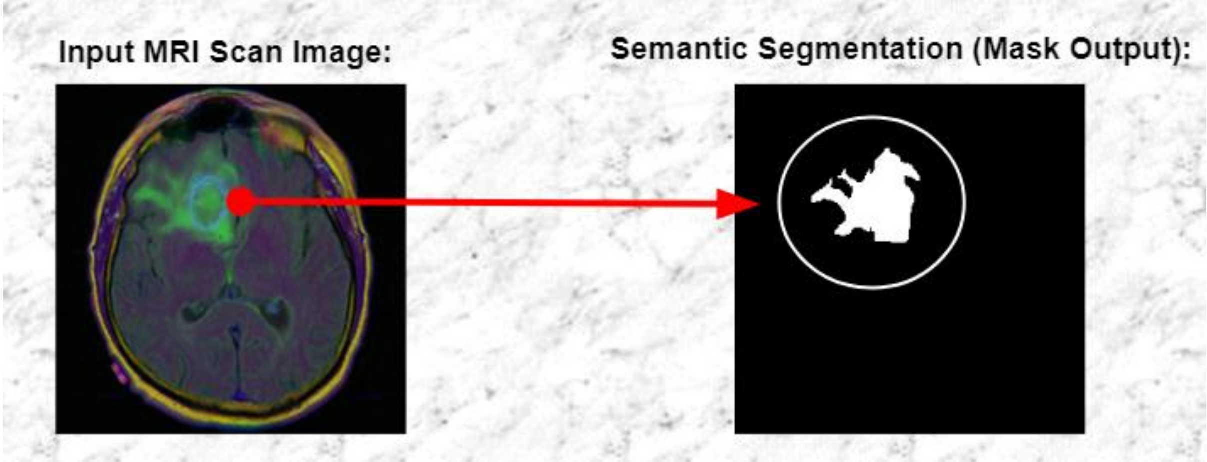
Introduction:

The project aims to tackle the challenging task of semantic image segmentation for medical images, including X-rays, CT scans, and MRIs, by leveraging deep learning techniques, specifically Convolutional Neural Networks (CNNs) with the U-Net architecture. The objective is to develop an accurate and efficient algorithm that can automatically identify and classify different anatomical structures and abnormalities within medical images.

Semantic image segmentation involves assigning a specific label or category to each pixel in an image, enabling precise identification of different structures or regions of interest. Deep learning, particularly CNNs, has demonstrated exceptional performance in various computer vision tasks, including image segmentation. The U-Net architecture, in particular, has proven effective in medical image analysis, as it incorporates both down sampling and up sampling paths, enabling the network to capture detailed information while preserving spatial context.

The project follows a comprehensive approach that includes the design and analysis of algorithms. Initially, a dataset of annotated medical images is collected and pre-processed to ensure consistent quality and format. The annotated images serve as ground truth, providing pixel-level labels for training and evaluation purposes.

The U-Net architecture is then implemented using deep learning frameworks such as TensorFlow. The network is trained on the annotated dataset, optimizing its parameters to minimize the segmentation error. This process involves forward and backward propagation of data through the network, adjusting the weights and biases of the CNN to improve performance.



To evaluate the algorithm's effectiveness, a separate validation dataset is used, consisting of unseen medical images. The trained U-Net model is applied to these images, and the resulting segmentations are compared with the ground truth annotations. Various evaluation metrics such as Dice coefficient, Jaccard index, or pixel accuracy are computed to measure the segmentation accuracy and overall performance.

The project also involves algorithmic analysis to address potential limitations and improve the model's robustness. This includes exploring techniques such as data augmentation, regularization, or network architecture modifications to enhance performance and generalization capabilities. Additionally, computational efficiency is considered by optimizing the implementation for faster inference, ensuring the algorithm can be deployed in real-time scenarios.

Overall, the project focuses on leveraging deep learning, specifically the U-Net architecture, to achieve accurate semantic image segmentation for medical images. Through the design and analysis of algorithms, the project aims to develop a reliable and efficient tool for aiding medical professionals in the precise identification and analysis of anatomical structures and abnormalities in a variety of medical imaging modalities.

Motivation:

The motivation behind this project is to revolutionize medical image processing for radiologists, streamlining their workflow and increasing efficiency while improving accuracy and providing a crucial verification step for diagnoses.

By implementing deep learning-based semantic image segmentation using CNNs with the U-Net architecture, radiologists can save time and effort by automating the identification of anatomical structures and abnormalities. This streamlined approach accelerates the diagnostic process, leading to faster results and improved patient care. The algorithm's high accuracy in segmenting medical images enhances precision, ensuring even the subtlest structures and abnormalities are detected, reducing the risk of oversight or misinterpretation.

Additionally, the algorithm serves as a valuable verification step, comparing its results with radiologists' initial analysis to minimize errors and increase diagnostic confidence.

Hence, this project aims to streamline and enhance medical image processing, enabling radiologists to provide more efficient, accurate, and reliable diagnoses.

Existing System:

Existing human counterparts for the semantic image segmentation project involving medical images are radiologists and medical imaging specialists. These professionals possess expertise in interpreting and analysing medical images, including X-rays, CT scans, and MRIs, and manually perform the task of segmenting and identifying anatomical structures and abnormalities. Radiologists are trained to visually inspect medical images, identify relevant regions of interest, and provide accurate diagnoses.

Currently, radiologists manually annotate and segment medical images, a time-consuming and labour-intensive process. They meticulously examine each image, identifying and labelling specific structures or abnormalities. Their experience and knowledge play a vital role in accurately identifying subtle or complex features within the images. Radiologists rely on their expertise to make informed judgments and provide diagnostic insights

Limitations of Existing System:

Existing systems for semantic image segmentation in medical imaging have some limitations. Firstly, manual segmentation by human experts is time-consuming and labour-intensive. It requires meticulous annotation and can be subject to human error and variability, leading to inconsistencies in results.

Secondly, the manual segmentation process is subjective and can vary among different radiologists. Inter- and intra-observer variability can arise due to differences in expertise, experience, and interpretation. This variability can impact the accuracy and reliability of the segmentation results, potentially affecting diagnostic outcomes.

Additionally, manual segmentation may not be feasible for large datasets or real-time scenarios where prompt analysis is crucial. The sheer volume of medical images requires automated solutions to expedite the segmentation process and enable efficient analysis.

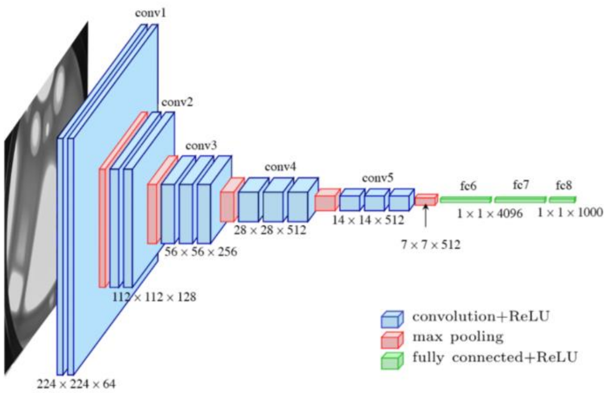
Moreover, human experts may face challenges in identifying subtle or complex structures, especially in cases where the abnormalities are difficult to detect visually. Human observers can also experience fatigue or overlook certain details, leading to potential diagnostic errors or missed findings. The limitations of existing systems highlight the need for automated and reliable algorithms based on deep learning techniques.

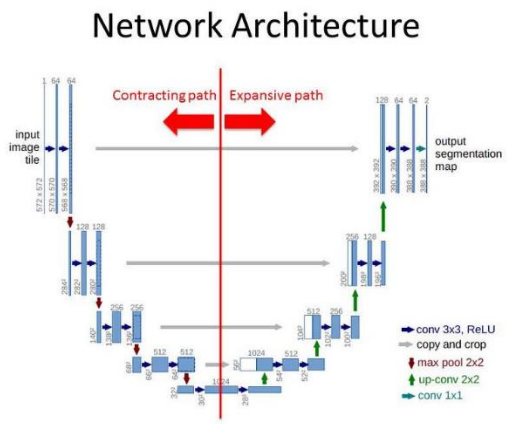
While human expertise is valuable, the semantic image segmentation project aims to automate and augment the work performed by radiologists. By leveraging deep learning techniques, the project seeks to develop algorithms that can perform image segmentation tasks with speed, consistency, and potential accuracy comparable to human counterparts. These automated solutions can enhance efficiency, reduce subjectivity, and serve as valuable tools to support and assist radiologists in their clinical workflow, ultimately improving patient care.

Proposed System:

Hence to overcome and increase the efficiency of the currently utilized system , a combination of large datasets , which are readily available due to the sheer volume of medical images taken on a daily basis , and a calculated Convolution Neural Network/Deep Learning model with specific accuracy metrics , loss algorithms and back propagation algorithms to achieve sensitive image segmentation model that can identify relatively small and large abnormalities in a certain image and hence classifying the image accordingly and allowing the doctors to do the needful.

Further the system can me improved by training on different datasets and feedback loop by using radiologists to verify the output of the system to make it more accurate and broader for the general user.





System Requirement Specifications:

The functional requirements of the proposed system include:

- A computer with a relatively good CPU and a GPU for the training systems only.
- Up to date python and TensorFlow and keras software.
- Large / Broad and clean datasets with RGB as well as masks channels.
- Image Preprocessing.
- CNN model training.
- Storage system for the outputs of the model and to store the continuously changing weights of the model.
- Integration and Development with various software.

The non-functional requirements of the proposed system include:

- High accuracy in training, validation as well as testing.
- Loss in training, validation and testing should be close and as low as possible
- User Friendly interface
- Scalable to larger and different devices
- High privacy and security of the medical details of an individual

Proposed Methodology:

Proposed Methodology for Semantic Image Segmentation in Medical Images using CNN with U-Net Architecture:

1.Data Collection and Preprocessing:

- Gather a diverse and representative dataset of medical images, including X-rays, CT scans, and MRIs, with corresponding ground truth annotations.
- Preprocess the dataset by applying necessary transformations, such as resizing, normalization, and noise reduction, to ensure consistent data quality.

2.Model Architecture Design:

- Design the CNN model architecture based on the U-Net framework, which consists of both down sampling and up sampling paths.
- Define the number of layers, filters, and activation functions for each module in the network, considering the complexity and resolution of medical images.

3.Training Data Preparation:

- Split the pre-processed dataset into training, validation, and testing sets.
- Augment the training data using techniques like rotation, flipping, or scaling to increase the variability and generalization capabilities of the model.

4.Model Training and Optimization:

- Initialize the CNN model with appropriate weights and biases.
- Train the model using the training dataset by optimizing the loss function, such as cross-entropy or dice coefficient, through backpropagation and gradient descent.
- Regularize the model using techniques like dropout or batch normalization to prevent overfitting.

5.Model Evaluation and Fine-tuning:

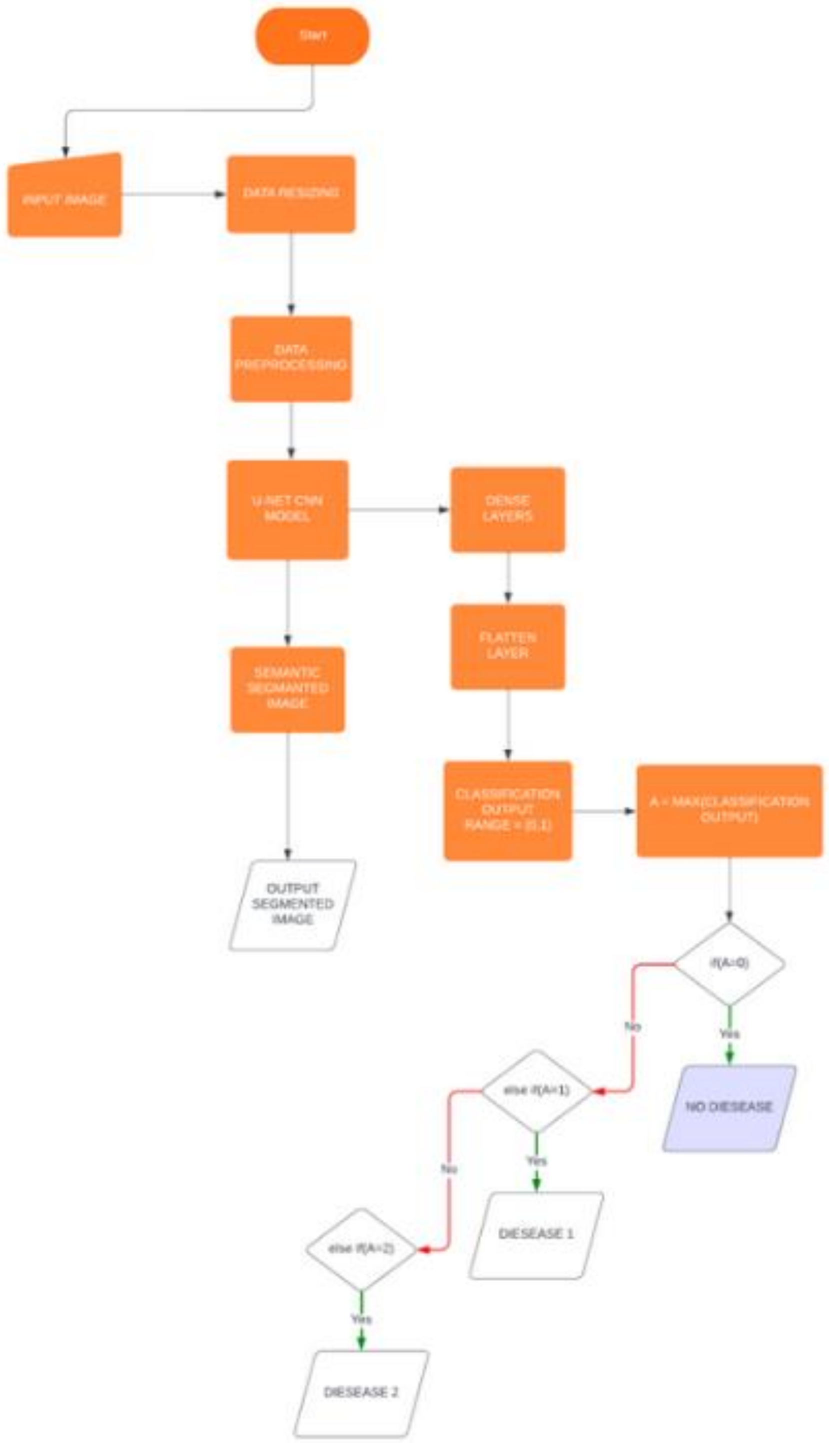
- Evaluate the trained model using the validation dataset, computing evaluation metrics such as Dice coefficient, Jaccard index, or pixel accuracy to measure segmentation performance.
- Fine-tune the model based on the evaluation results, adjusting hyperparameters, such as learning rate or weight decay, to further enhance performance.

6.Testing and Deployment:

- Assess the final model's performance on the testing dataset to validate its generalization capabilities.
- Integrate the trained model into a software application or system that allows users, such as radiologists, to input medical images and obtain segmentation results.
- Optimize the model and the implementation for efficient real-time or near-real-time inference to enable quick and seamless integration into clinical workflows.

Throughout the methodology, it is essential to follow best practices in deep learning, including appropriate data handling, model evaluation, and iterative refinement, to ensure the development of a robust and accurate semantic image segmentation system for medical images.

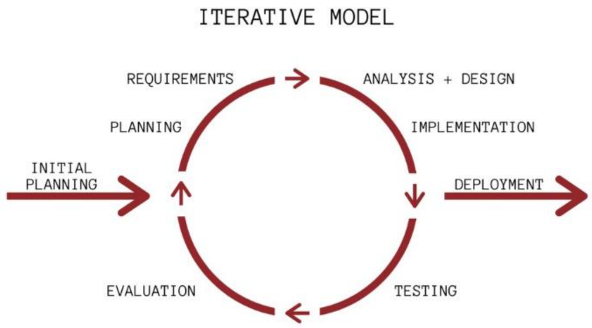
Activity flow Diagram:



Software Engineering Model Used:

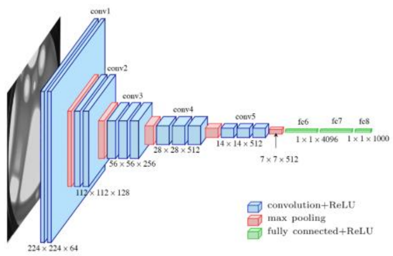
The Iterative model is used in this project, since we loop continuously between training, testing and accuracy, fine tuning the Neural Network by adding dropout, dense, flatten layers at different instances to get high accuracy in the results.

Finally, the best model gets deployed and integrated with the Graphical User Interface and hence to the end user

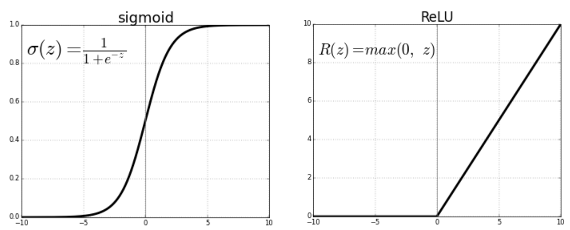


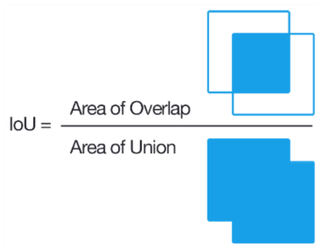
Algorithm Implemented (DAA concept):

Divide and conquer method is implemented in Convolutional Neural Networks wherein pixels of Single image is split in smaller grid of specified size and that is analysed for features such straight lines or curves depending on the input, then the a resultant image is output with higher values for the pixels with required feature map.



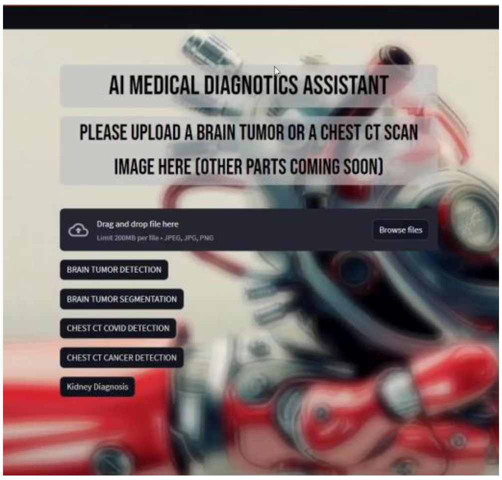
Further localization functions such as IoU (intersection over union), Gradient descent and loss functions such as Cross entropy loss and focal loss are used for localizing or locating a certain feature in the input image. Sigmoid, Relu and Softmax functions are used as activation functions to create fuzzy set outputs which range from 0 - 1.



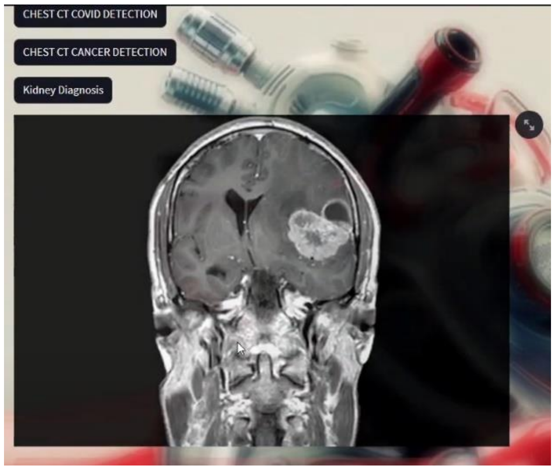


Implementation:

Landing Page:

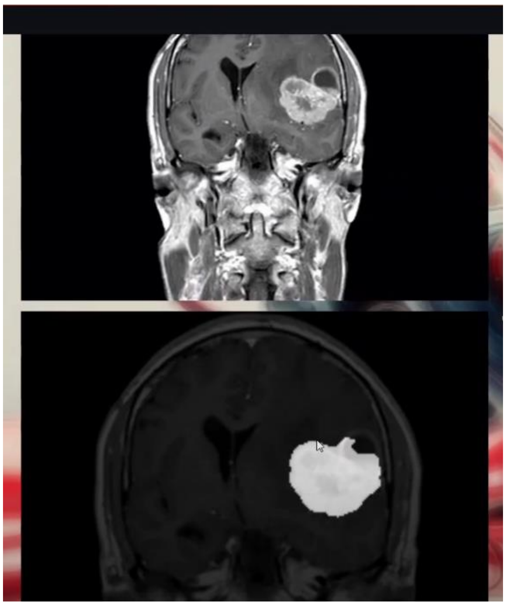


Upload Scan Image:



Detection:

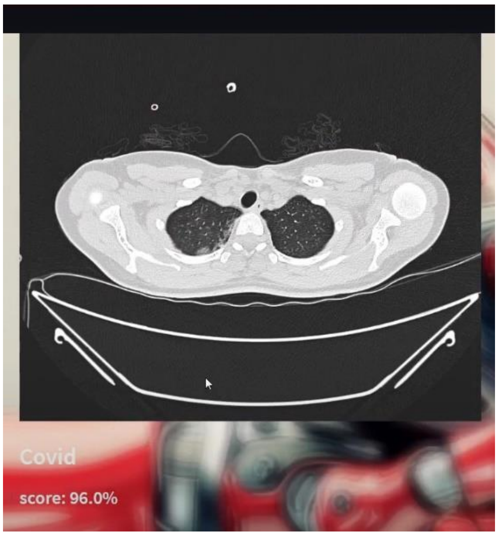
Segmentation:



As shown above, upon going on the landing page, a file containing the scan image is asked to be uploaded and then a wide range of options to detect and segment are available. On clicking one of these options the appropriate results are shown as shown.

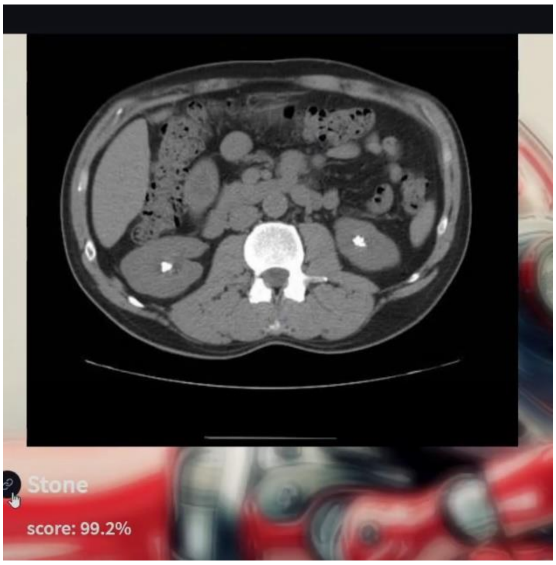
More examples of detection for other types of scans:

Chest CT covid detection:

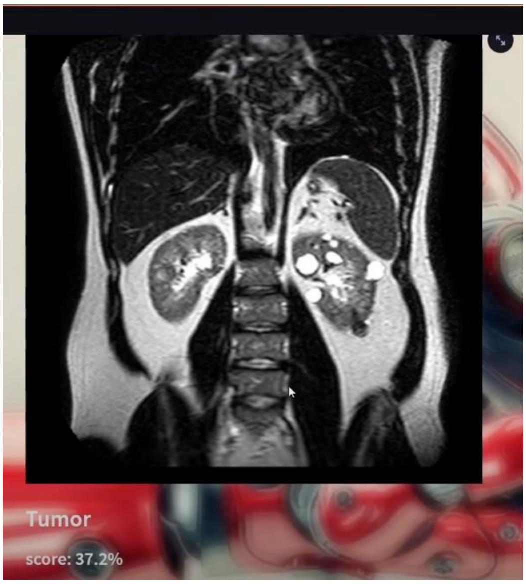


Chest Cancer detection:

Kidney Diagnosis:



Kidney Diagnosis:



Novelty of the project:

Deep learning and AI haven't yet made an impact on the medical field; hence this project aims to integrate Deep learning into the large-scale medical field as well as to the general public, making information accessible to all and the process of diagnosis efficient.

However, there are many research papers on the implementation of deep learning for medical sectors but our project aims to implement these results in large scale and make it accessible to all. Our project also aims to run on low resources and still provide high accuracy and consistency, hence eliminating the need to use cloud-based systems and hence increasing the security and privacy of the system.

Therefore, while there are many systems that are researching and developing the integration of DL and AI in the high level of the medical sector, our project aims to use existing technology and architectures and automate the menial/mundane tasks in the medical sector and further make information accessible to all, making it easy to know about one's body.

Future Enhancements:

● Short Term Enhancements:

○ More models for different parts of the body and train a model for accurate segmentation of image.

○ Existing models can be trained for different diagnosis for the same body image.

○ The Training Models can be updated to Residual-Unet or Attention Unet for better consistency and accuracy.

● Long Term Enhancements:

○ The models can be actively trained upon the feedback of the user after they have trained on the model (Essentially a Feedback Loop) And hence increasing the consistency and accuracy

○ The feedback loop can also be used to detect anomalies that haven't yet been discovered.

○ Further, the model can be deployed directly into the medical imaging machines that can provide the original data and a predicted segmented and classified data. This can act as a helping hand to the doctors classifying the data.

○ A similar model for 3 dimensions, i.e., 3D U-Net can be used for 3D MRI slices to obtain a 3-dimensional segmentation of the tumor. This can further be used in Augmented Reality Systems to help surgeons locate the tumor in real time while the surgery is going on.

References:

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2. https://www.inf.ufpr.br/todt/IAaplicada/CNN_Presentation.pdf