AUTOMATIC SEGMENTATION & CLASSIFICATION OF CT LIVER TUMOR IMAGES USING CNN MODEL

PHASE II REPORT

Submitted by

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in partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING

IN

COMPUTER SCIENCE AND ENGINEERING

RAJALAKSHMI ENGINEERING COLLEGE

ANNA UNIVERSITY, CHENNAI

MAY 2024

RAJALAKSHMI ENGINEERING COLLEGE
CHENNAI

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ACKNOWLEDGEMENT

Initially we thank the Almighty for being with us through every walk of our life and showering his blessings through the endeavor to put forth this report. Our sincere thanks to our Chairman **Mr. S.MEGANATHAN, B.E, F.I.E.**, our Vice Chairman **Mr. ABHAY SHANKAR MEGANATHAN, B.E., M.S.,** and our respected Chairperson **Dr. (Mrs.) THANGAM MEGANATHAN**, **Ph.D.,** for providing us with the requisite infrastructure and sincere endeavoring in educating us in their premier institution. Our sincere thanks to **Dr. S.N. MURUGESAN, M.E., Ph.D.,** our beloved Principal for his kind support and facilities provided to complete our work in time. We express our sincere thanks to **Dr.P.KUMAR, Ph.D.**, Professor and Head of the Department of Computer Science and Engineering for his guidance and encouragement throughout the project work. We convey our sincere and deepest gratitude to our internal guide, **Dr. B. Vijayalakshmi** Department of Computer Science and Engineering. Rajalakshmi Engineering College for her valuable guidance throughout the course of the project. We are very glad to thank our Project Coordinator, **Dr.N.Duraimurugan** , Department of Computer Science and Engineering for his useful tips during our review to build our project.

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ABSTRACT

Liver tumors rank as the third deadliest cancer globally and the sixth most prevalent disease worldwide. They primarily afflict individuals who frequently consume tobacco or alcohol. Approximately 75-85 percent of primary liver cancer cases are attributed to these factors. However, manually diagnosing liver tumors presents significant challenges due to tumor heterogeneity, varying shapes and sizes, imaging artifacts, and limited annotated data.The critical task of segmenting liver tumors in medical images greatly impacts diagnosis and treatment planning. Numerous techniques and frameworks have been formulated for the early identification of tumors, improving accuracy, and aiding doctors in understanding tumor characteristics such as size and volume. Nevertheless, this process is error prone and cumbersome.To address these challenges, a proposed solution utilizes Deep Learning (DL) with the TransUNet model, a Convolutional Network (CNN), for real-time picture processing. This system assists doctors in swiftly identifying and segmenting tumors from images, providing an approximation of tumor size and stage for more precise treatment. In summary, liver tumors are a major global health concern, often linked to alcohol and tobacco use. Manual diagnosis is challenging, but advanced DL methods like TransUNet help with early detection and tumor segmentation, assisting doctors in providing timely and accurate treatment.

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LIST OF ABBREVIATIONS

DL- Deep Learning

CNN- Convolutional Neural Networks

HCC- Hepatocellular Carcinoma

CT- Computed Tomography

UI- User Interface

UML- Unified Modeling Language

CHAPTER 1
INTRODUCTION

Tumors globally have been a major cause of death in various parts of the globe and have been deadlier at each turn and the statistics shows that around 8 lakh people are being affected especially by Liver tumors every year and the total death rate of cancer is around 10 million around the globe. Even more advancements and researches are being conducted to detect and cure tumors. A specific percent of tumors are either undiagnosed or diagnosed lately, preventing the option of curing the tumor.

1.1 GENERAL

Undiagnosed liver tumors lead to various problems and are considered to be fatal. The tumor slowly spreads all over the parts of the liver and starts damaging the intestines and turning it into a huge havoc. The early identification, treatment, and patient care of liver cancer, a serious worldwide health problem, present substantial difficulties. Effective treatment planning and prognosis assessment depends on the precise segmentation and delineation of liver tumors using medical imaging data.

1.2 OBJECTIVE

Manual segmentation requires a lot of time and a lot of expertise in that specific matter and not everyone will be able to do it. In order to help doctors evaluate the features, size, form, and therapeutic response of liver tumors, liver tumor segmentation entails the exact delineation of tumor borders. Various measures such as CT imaging, ultrasound, MRI scans are frequently employed to detect liver tumors at preliminary phases to provide appropriate treatment and solve the issue. These scans provide the severity of the tumors or the developing stage of the tumors to the doctor and help in diagnosing them by segmenting the tumor parts. Also it helps to achieve detailed segmentation for outlining liver tumor boundaries to improve treatment strategies.So the main objective is to utilize an effective model in order for effective segmentation of liver tumors and segment the given images according to requirement.

1.3 EXISTING SYSTEM

Previously implemented models have used various algorithms such as U-Net, ResNet, Statistical shape models and various such algorithms. Various systems focused on the accuracy and the improvement of the performance of the working of systems and in each turn different models have shown a better accuracy and performance than previous state of art. Many implemented systems clearly have different scopes and different modules in comparison with each other.

1.4 PROPOSED SYSTEM

Most researchers used CNN and differed with U-Net, RES-Net, and various modified algorithms and other machine learning algorithms. The proposed system uses the transformers methods in the TransUNet model providing advantage as it is proven that transformers are better encoders and decoders in the medical imaging processes and have better performances than other imaging models.

The proposed system here is the segmentation of liver tumors utilizing CNN model for effective processing of the image samples of liver tumor datasets using the TransUNet model. The main focus is to develop a web application with an appropriate User Interface that allows users to enter their images as input. The input data is analyzed and segmented into different layers as livers and liver tumors, and the severity of tumors is analyzed by checking various parameters such as volume, size, etc.

These segmentation and analytics are completely performed by the Deep Learning model TransUNet deployed. When the images are segmented and analyzed properly, the new factor of finding the size of the tumor is added to analyze the stage of the tumor of the provided input. The tumor size is calculated with appropriate formulas and calculations, and depending upon the size obtained from the size calculation, the stage of the tumor, the user is intimated about the stage of the tumor that the user might possibly have, along with the other obtained results from segmentation and analytics. In the end, the user is provided with information such as if the tumor is malignant or benign and all other important parameters such as tumor size. This application’s targeted users are medical professionals and provides an overview of the tumor of the patient helping them to decide the ideal treatment for the respective patient.

CHAPTER 2
LITERATURE SURVEY

[1] Amritha. M, Manimegalai. P "Liver Tumor Segmentation and Classification Using Deep Learning"

The researchers delved into the realm of segmentation of Liver tumors and classification through the lens of deep learning. The paper highlights the pivotal role of intense learning methodologies in increasing the accuracy and efficiency of liver tumor diagnostics. Leveraging a possibly extensive dataset of liver imaging scans, the authors compared the efficacy of their proposed deep learning-based techniques with existing conventional methods. Addressing potential challenges in tumor variability and imaging inconsistencies, the team showcased the optimized capabilities of their deep learning approach. This research illuminates the advancements in liver tumor diagnostics using previous computational methods, emphasizing the transformative potential of deep learning in medical imaging.

[2] A. P R and L. T M, "Automatic segmentation and classification of the liver tumor using deep learning algorithms,"

This research proposed an automated system for identification of liver tumors utilizing deep learning processes. This system integrates segmentation, where liver and tumors are isolated from surrounding tissues, followed by a classification mechanism to differentiate benign from malignant tumors. Addressing challenges such as tumor heterogeneity and variations in appearance, the authors optimized their models, showcasing the transformative potential of deep learning in the early finding and treatment of liver tumors.

[3] A. Patel, K. Prateek and S. Maity, "A W-Net Based Architecture with Residual Block for Liver Segmentation,"

The study accentuates the strength of integrating W-Net, a potentially modified version or an extension of the U-Net architecture, with residual blocks, which are known to facilitate deeper network training by mitigating the vanishing gradient problem. This combination aims to enhance the accuracy and efficiency of liver segmentation tasks.The integration of residual blocks within the W-Net framework is highlighted as a significant advancement, potentially leading to better feature extraction and improved segmentation outcomes.

[4] A. R and A. L, ”Effective Methods to Detect Liver Cancer Using CNN and Deep Learning”

The authors delve into the deep learning algorithms to liver cancer. Their study emphasizes the need for reliable liver cancer detection approaches, as well as the promise of CNNs in improving detection. diagnostic precision.The study contrasts the capabilities of deep learning algorithms with traditional diagnostic techniques. This research underscores the pivotal role of advanced deep learning techniques, particularly CNNs, in revolutionizing liver cancer diagnostics.

[5]B. Chen, Y. Chen, G. Yang, J. Meng, R. Zeng and L. Luo, ”Segmentation of liver tumor using nonlocal contours,”

This paper represents a segmentation method for liver tumors depending on nonlocal active- contours, this paper emphasizes the algorithm’s robustness. It addresses challenges related to tumor characteristics but suggests further research to enhance its accuracy and efficiency in tumor segmentation tasks.

[6] C. G., Schenk, A., Moltz, J.H. *et al.* Automatic liver tumor segmentation in CT with fully convolutional neural networks

This study describes the 2D CNN approach with the post object processing phase. They used two working models, voxel and object-level, to calculate the decrease of incorrect results. The appropriate items are discovered and segmented, and post-processing completely identifies the segmented tumor.

[7] Krishnakumari, L., Ramalakshmi, R., Srirenganachiyar, V., Ragavan, K., \& Ramalakshmi, K. (2023). Analysis of Liver Tumor Segmentation using Deep ResUNet. 2023 Third International Conference on Artificial Intelligence and Smart Energy (ICAIS), 665-668.

The team undertook an in depth analysis of segmentation of tumor leveraging the capabilities of Deep ResUNet.The study highlights the significance of exact segmentation in the early finding and treatment of liver tumors. Using a relevant dataset, presumably including liver imaging images, the authors demonstrate the benefits of employing Deep ResUNet, a fusion of Residual Networks and U-Net architectures, over conventional segmentation methods. Through their results, the study underscores the efficacy and potential of the Deep ResUNet architecture in advancing medical imaging diagnostics and offers significant insights into its applications for liver tumor detection.

[8] .L. Hong, R. Wang, T. Lei, X. Du and Y. Wan, ”Qau-Net: Quartet Attention U-Net for Liver and Liver-Tumor Segmentation,”

The authors provide the "Qau-Net: Quartet Attention U-Net for Liver and Liver-Tumor Segmentation" model. The Qau-Net employs a one-of-a-kind "Quartet Attention" mechanism, implying a sophisticated approach to focusing on significant characteristics throughout the segmentation process. The integration of this attention mechanism with the current U-Net architecture is particularly interesting, as it attempts to improve segmentation performance in medical imaging data for liver and tumor areas. The study indicates the efficiency of the Qau-Net in comparison to other cutting-edge technologies, indicating a potential improvement in the field of liver-related medical picture processing.

[9] M. Rela, N. R. Surya and P. R. Reddy, ”Liver Tumor Segmentation and Classification”

This research paper uses Multi Gabor Feature and non local active contours. The feature map is used for texture analysis and edge detection primarily for tumor detection. This feature map refers to a set of array of gabor filters applied to images to extract the necessary features under various perspectives. With using the given model, the performance is considered to be better than other previous models.

[10] M. Sato, Z. Jin and K. Suzuki, ”Semantic Segmentation of Liver Tumor in Contrast-enhanced Hepatic CT by Using Deep Learning with Hessian Based Enhancer”

The paper represents a 3D MTANN model that combines with a Hessian dependent enhancer on the basis of accuracy and efficiency, though it acknowledges the need for further validation on larger datasets and comparison with other segmentation methods.

[11] Mr.Napte, & Mahajan, Anurag. (2021). Liver Segmentation and Cancer Detection Based on Deep CNN

The authors map the academic landscape, identifying major contributors, seminal papers, and prevailing trends in the domain. The bibliometric survey serves as a consolidated guide, presenting insights into the progress, problems, as well as future directions in the field of

DCNN-based liver segmentation and cancer detection. Such an analysis is invaluable for researchers and practitioners in the field, offering a structured overview of existing literature, highlighting knowledge gaps, and suggesting potential avenues for future exploration in the domain of medical imaging and liver diagnostics.

[12] M.Rela , S.N.Rao and Patil Ramana Reddy “Performance analysis of liver tumor classification using machine learning algorithms”

The authors use machine learning methods to systematically examine the performance of liver tumor categorization. The study delves deeply into the problems and complexities of liver tumor diagnoses, highlighting the revolutionary potential of machine learning in improving diagnostic accuracy and efficiency.Throughout their study, they address the obstacles inherent in liver tumor heterogeneity and classification complexities, leading to optimized machine learning approaches. This study emphasizes the improvements and crucial significance of machine learning in liver tumor diagnoses, giving both a complete review and prospective future prospects.

[13] P.Bilic.Christ, Hongwei Bran The Liver Tumor Segmentation

The paper delves deep into the intricacies of tumor segmentation. The ”LiTS” benchmark serves as a comprehensive evaluation platform, showcasing the cutting-edge approaches and strategies for segmenting liver tumors. Through rigorous evaluations and comparisons, the benchmark provides information into the performance and efficiency of various segmentation techniques.The outcomes from this benchmark serve as a hint point for current and possible future research endeavors, setting standards in the domain of segmentation of tumor offering guidelines for advancements in the field.

[14] ”A Multi-layer U-Net for CT-based Liver and Liver Tumor Segmentation”

This work employs the U-Net model and the Un-Net model, in which pictures are segmented appropriately using relevant features and significantly outperform other metrics using other models, and the employment of these models has shown to be superior to earlier methods.The main idea of the research is to accurately separate both the liver and tumors in CT images using deep learning techniques. Accurate segmentation is vital for various medical applications such as treatment identification, surgical ideology, and disease monitoring.The proposed Un-Net likely involves enhancements or modifications to the traditional U-Net architecture, potentially incorporating multiple layers or other novel design elements. These modifications could aim to improve segmentation accuracy, robustness, or efficiency compared to standard U-Net architectures.

CHAPTER 3
SYSTEM DESIGN

3.1 GENERAL

3.1.1 SYSTEM FLOW DIAGRAM

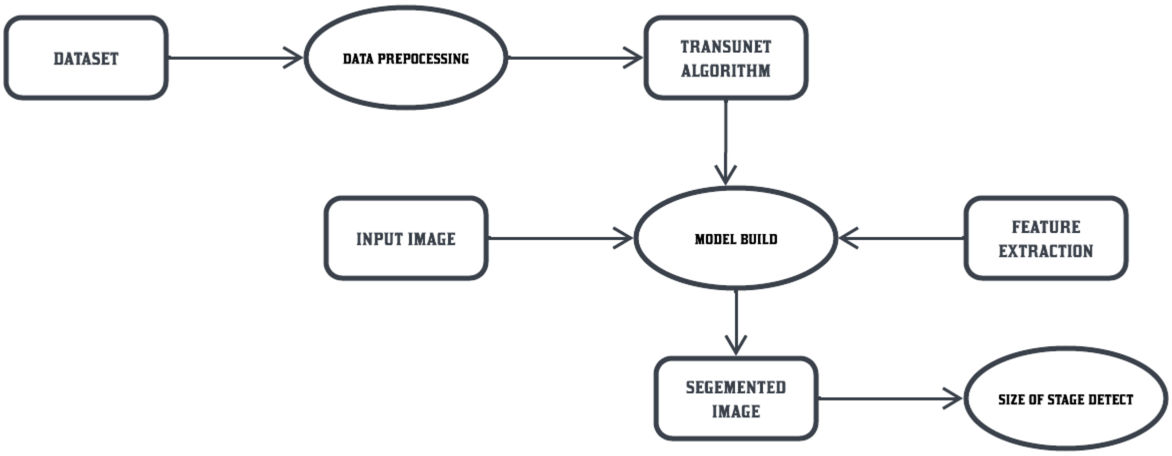

Fig 3.1.1 System Flow Diagram

It is a high-level diagram that provides an overview of how different components in a system work together to achieve a particular goal or deliver a specific functionality. System Flow Diagrams are used in systems engineering and software development to communicate the architecture, functionality, and flow of information within a system. System Flow Diagrams are particularly useful during the starting stages of system design and analysis to ensure a shared understanding among stakeholders about how the system will operate. They serve as a valuable communication tool between technical and non-technical team members, helping to convey complex system architectures in a more accessible format.

Many deep neural networks trained on images have a curious phenomenon in common: in the early layers of the network, a deep learning model tries to learn a low level of features, like detecting edges, colours, variations of intensities, etc. Such kind of features appear not to be specific to a particular dataset or a task because no matter what type of image we are processing either for detecting a lion or car.

In both cases, we have to detect these low-level features. All these features occur regardless of the exact cost function or image dataset. Thus, learning these features in one task of detecting lions can be used in other tasks like detecting humans.

The proposed system flow diagram depicts the complete flow on how the process works and how data is transferred to the next stage for appropriate processing to obtain required output and obtain the segmented tumor parts and calculate the tumor sizes. Starting with the user uploading the CT images of the liver scans for processing. This image is passed on to the preprocessing part where various filters such as histogram equalization, edge detection methods and Data augmentation methods etc in order to help in the segmentation process. After preprocessing the images, they are shared to the TransUNet model for segmentation process and the results are obtained after segmentation.

After segmentation processes, images are segmented randomly and no proper classification will be obtained. So classification of images will be processed for segmented images using the classified datasets from the database and using this process segmented tumors are recognised and processed for tumor size calculation. The segmented tumors are sent for tumor size calculation and using the appropriate formulas in pixel methods the size of liver tumor is found. Depending on the obtained size of the tumor, the stage of the respective tumor is decided , for provided scans, is displayed in the web browser as results. Along with the tumor size and the tumor stages are displayed to the user, the segmented tumors are also displayed for user reference and information regarding the tumor stages will also be displayed for user information. In this way the whole system process flow is carried out.

3.1.2 ARCHITECTURE DIAGRAM

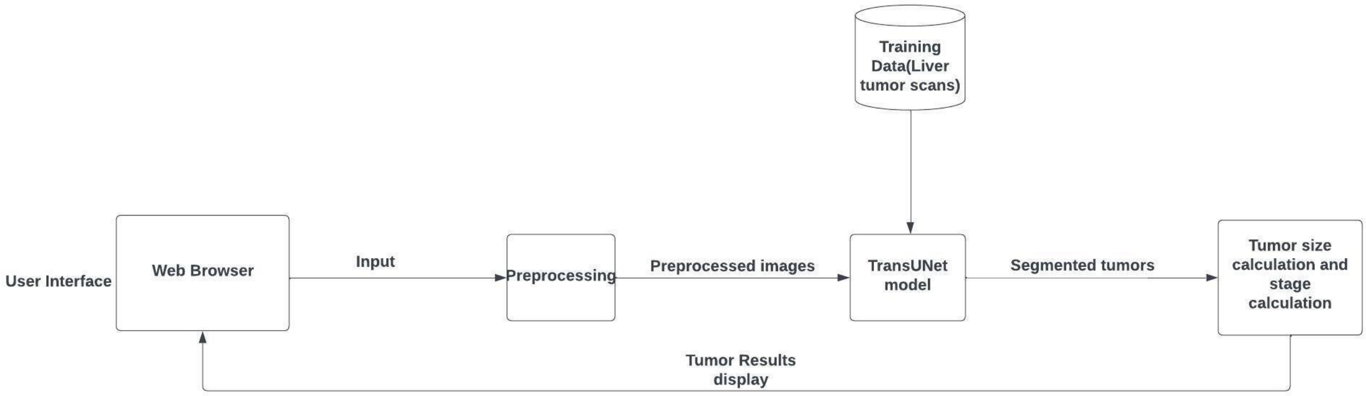

Fig. 3.1.2 Architecture Diagram

An architecture diagram is a representation of the structure of a system, showing the key components or modules and their relationships. It gives the overview of how various parts of a system interact and work together to achieve a specific set of functionalities. For the proposed system the architecture diagram represents what are the processes involved in the system and how the process will be carried out. Starting with the user input by the user using the provided interface in the web browser, the provided input is moved for preprocessing i.e reducing the noise in the images and increasing contrast and increasing the data volume by augmentation and performing other filters in order to perform flawless segmentation and make the process simple. After the preprocessing is done, the obtained results of preprocessed images are transferred to the TransUNet model for liver and tumor segmentation depending on user input and the segmentation will be done efficiently. This segmentation is carried out after the model is trained using the datasets that are stored in the database with labeled datasets for segmentation and classification processes. After the segmentation process, the segmented images are processed for classification as the images are random and tumors should be classified for size calculation. Once the size is calculated the complete results obtained in the process will be displayed in the web browser. The results displayed will be the tumor size, tumor stage and the segmented tumor part for the given input.

3.1.3 USECASE DIAGRAM

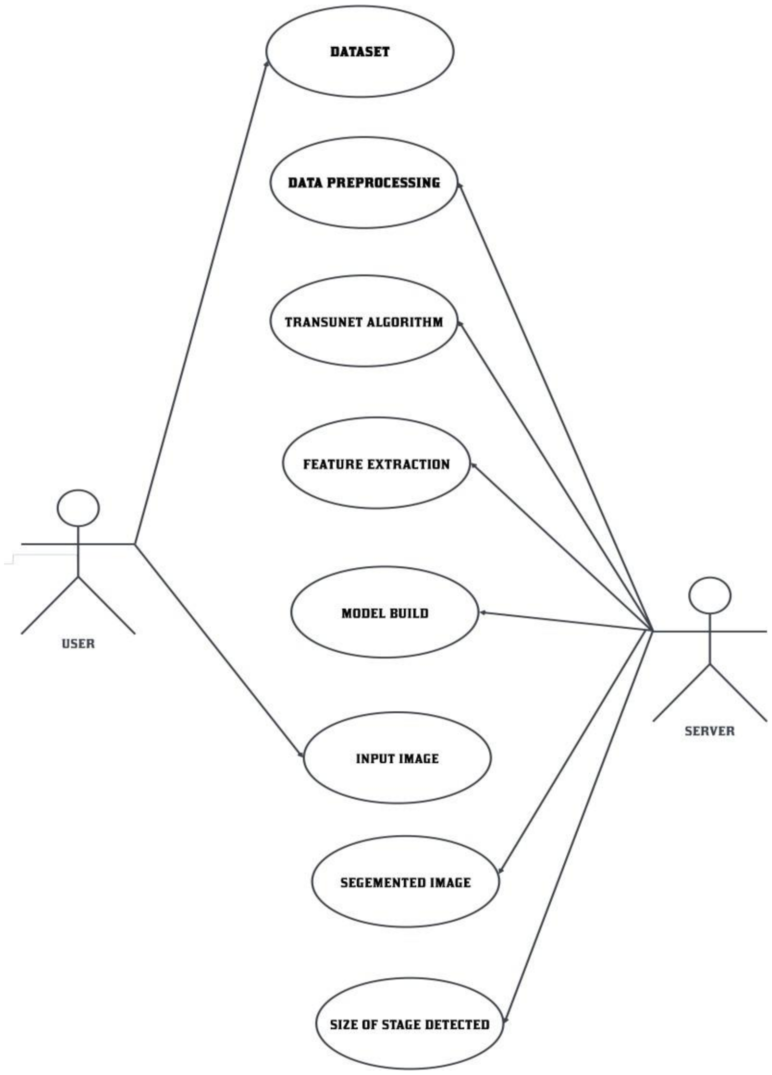

Fig 3.1.3 Use Case Diagram

It represents the different ways users interact with a system to perform specific tasks or goals. Here there are three actors namely the user, backend and the system performing all the prescribed processes in the code. Each actor accesses different use cases and not all actors use every aspect of the system. Here the user needs only the input in the browser page and expects the results in the web browser. The remaining processes are carried out by the system. Once the input is given, the system performs the preprocessing methods mentioned in the system code and makes the image noise free. Once it's done, the data will be shared to the TransUNet model, and which is accessed by the system. The model segments the given user image based on the datasets it has been trained using the datasets in the database. Here the backend actor works. Once the images are segmented by the model, the images are random and in order to find the tumor, the segmented will be processed to find the tumor stage and once the tumor size is found, depending on the result of tumor size,tumor stage is determined.

3.1.4 ACTIVITY DIAGRAM

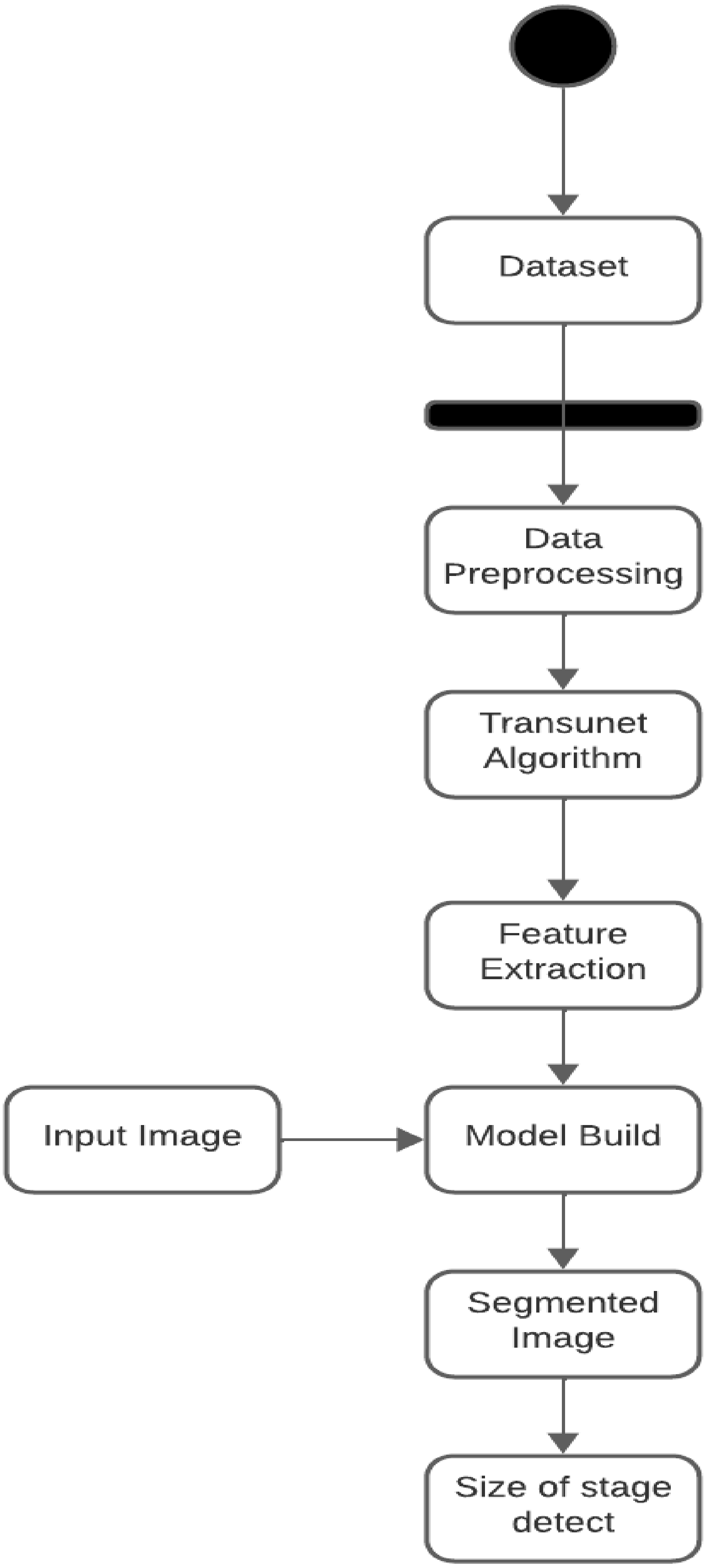

Fig 3.1.4 Activity Diagram

It is especially effective for modeling a system's dynamic characteristics, such as the order of operations and the decision points involved. Sequential and concurrent actions can be represented using activity diagrams. The segmentation activity diagram for liver tumor project is a visual representation of the workflow for segmenting liver tumors in medical images. The diagram shows the different steps involved in the workflow, as well as the flow of data between the steps.For the proposed system, from the start the user gathers the required datasets and scans to gain results and provide the input in the web browser, using the input method and sharing the image for further processing.

By starting the activity, the process starts with hosting the web browser and provides the interface for the user to upload the CT scans of liver scans to obtain the segmented tumors. Once the user uploads the CT scans the images are proceeded for preprocessing. The processes are combined from the browser and to proceed for further process. Once reaching the preprocessing node, the filters such as histogram equalization, data augmentation and edge detection methods etc. reduce the noises in the image to help in the segmentation process. Once the preprocessing steps are done, the image is suitable for the segmentation process, the trained TransUNet model starts the segmentation process. The model is trained using the labeled datasets for segmentation process. Once the segmentation of the images are done the images are combined for the classification of the images and classification is done in order to differentiate the segmented tumors and liver parts in order to calculate the tumor size.

Once the segmented images are classified based on the labeled dataset in the backend, they are moved further to calculate the tumor sizes. After classification the segmented tumors are moved further for tumor size calculation. After every stage, all the obtained results are combined in every stage and in reaching the tumor size calculation, the size of liver tumor is calculated based on pixels from segmented images, and with labeled datasets, the size will be calculated, the tumor size, tumor stage and the segmented tumor part are all displayed in the user interface.

3.1.5 SEQUENCE DIAGRAM

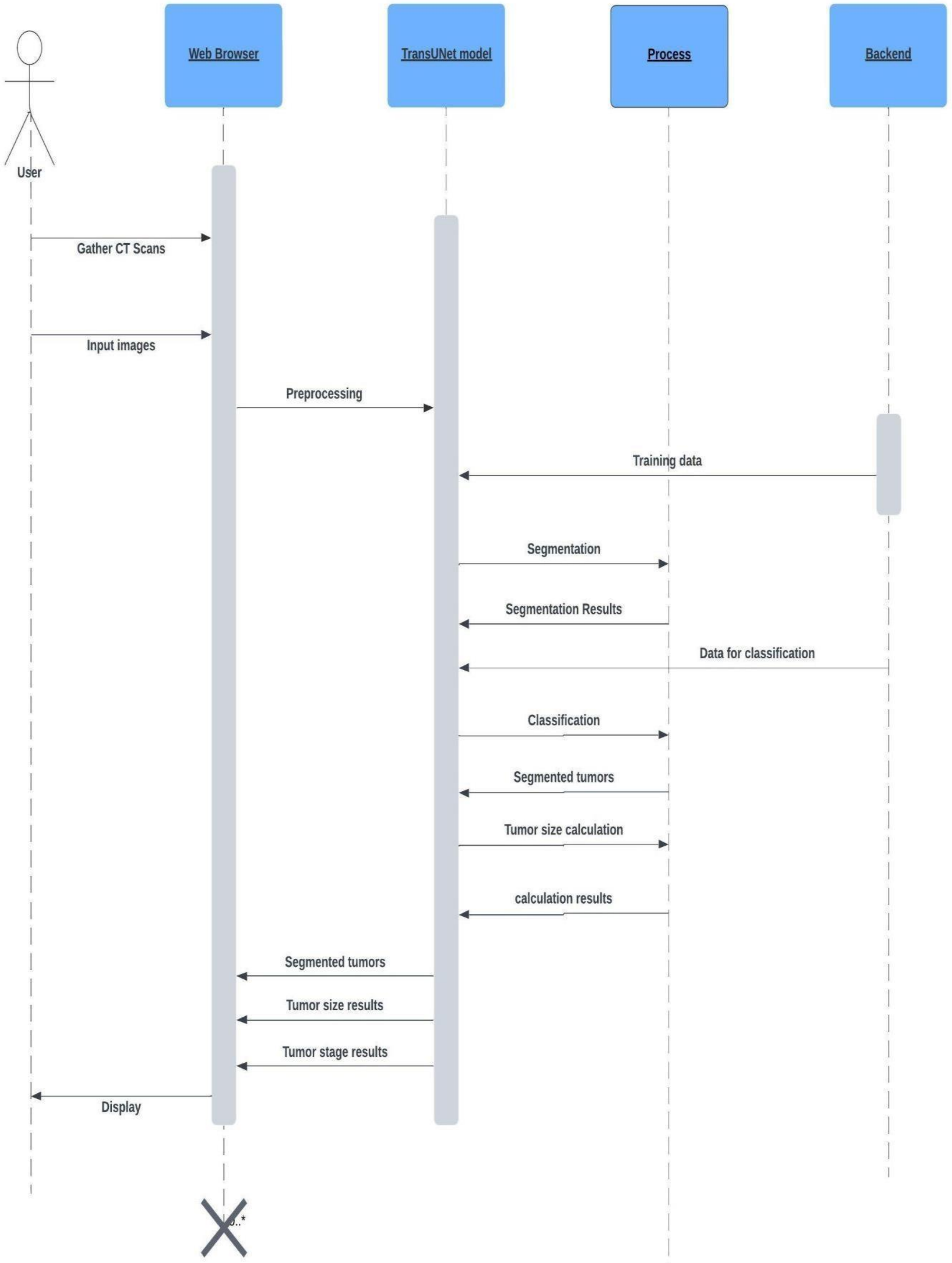

Fig 3.1.5 Sequence Diagram

A sequence diagram illustrates the interactions and dynamic behaviors among a set of objects or components within a system. It represents a sequence of interpretations shared between these subjects over time, showing the way in which the sharing occurs. Sequence diagrams involve the sequence of steps and the flow of interaction between different steps. The sequence starts with the user collecting the CT images and after gathering, input the images to the system using the web browser. Once the images are uploaded, the preprocessing step is taken over. The preprocessing step involves the filters in preprocessing methods to reduce the noises in images and give the preprocessed images to the TransUNet model for better performance in the segmentation process. On the other hand, the labeled datasets saved in the database will be utilized to practice the TransUNet model.

The model will be made to segment the given image and after the images will be segmented the classification processes will be started. The process follows the segmentation method and once the segmentation is completed the results will be processed further for classification methods. The segmented images are classified respectively as tumors or liver parts etc for tumor recognition. Once the classification is done, the segmented tumors are obtained for size calculation. The size of liver the tumors will be calculated based on pixel segmentation and the tumor size will be calculated to depict the stages.

Once the tumor sizes are calculated, the stages of the tumors are depicted based on the obtained tumor size with the prescribed metrics of tumor sizes. After obtaining all the results, the obtained results will be displayed for the user information. The details such as tumor size, tumor stage and the segmented tumor part will be displayed for the user information. In this case, all of the processes are performed in the prescribed order to get the desired results. The sequence diagram displays the messages and steps involved in each process and explains the data flow and messages between each process. Sequence diagram provides the user with a complete idea on how the process works and explains how the data is transferred between the processes and sharing the resource data and how the processes communicate with each other.

3.1.6 CLASS DIAGRAM

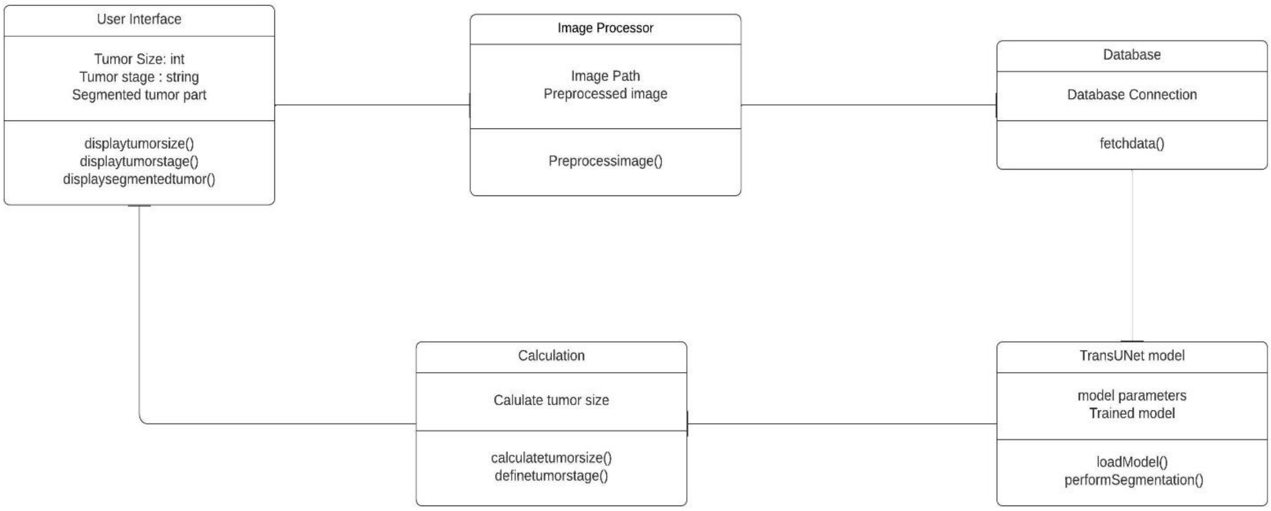

Fig 3.1.6 Class Diagram

It provides a static interpretation of the system, showing the design and organization of the various components that make up the system. Class diagrams are widely used in software engineering for designing and visualizing the structure of object-oriented systems. Here different classes include User Interface, Image Processor, database, TransUNet model, Classification processor, Calculation. The class diagram explains how the classes are connected to each other and how they use the attributes of other classes and explains the process.

The attributes of each class are depicted first and below the attributes are the operations carried out in the class modules. User Interface is associated with image processor whereas the calculation brings out the results to the user Interface to bring the results for the user. In each class, the operations mentioned carry out the process functions which they are predefined to carry out to obtain the desired results. Each attribute from a different class mentions what is the required input or the data to perform the operation in that specified class. Once the mentioned attributes are obtained the operations will be performed and will be moved to the further step. Each class is connected to each other in different ways and not all classes are connected to others in similar ways.

CHAPTER 4
PROJECT DESCRIPTION

The Liver Tumor Segmentation project focuses on developing a robust and accurate system for the automated segmentation of liver tumors in medical imaging data. Leveraging advanced image processing and deep learning techniques, the project seeks to enhance the efficiency and precision of tumor detection, providing valuable support to medical professionals in diagnosis and treatment planning. The Liver Tumor Segmentation project seeks to make a substantial contribution to medical imaging by improving healthcare practitioners' abilities in the findings and treatment of liver tumors. The project focuses to increase the efficiency of tumor segmentation operations by implementing sophisticated technology and a user-centric design.

4.1 METHODOLOGIES

Methodologies, refer to systematic, organized approaches or frameworks for accomplishing a particular task or achieving specific objectives. In various fields, the term "methodology" is used to describe a set of principles, practices, procedures, and rules that guide a process or method for conducting research, managing projects, or solving problems. Methodologies provide a structured way to plan, execute, and control activities, fostering consistency, repeatability, and efficiency. The methodology used here is the usage of CNN algorithm for the better Image processing performance. CNN has mostly been employed in medical applications and for imaging purposes and segmentation purposes. Under CNN model, the TransUNet model will be utilized for segmentation purposes and after segmentation respective classification methods will be utilized in order to classify and organize the segmented tumors.

4.1.1 MODULES

A module description for a project involving the segmentation of liver tumors typically outlines the different components or modules that make up the overall system. Each module represents a distinct functional unit with specific responsibilities. The module description outlines the characteristics, functionalities, and specifications of a specific module within a larger system or project. In software engineering and system design, a module is a self-contained unit of code or functionality that performs a specific task or provides a set of related features. A module description provides a detailed overview of what the module does, its interactions with other modules, and How it adds to the system's ultimate goals.

The proposed system contains the following modules:

4.1.1.1 Data Preprocessing

4.1.1.2 TransUNet model

4.1.1.3 Feature Extraction

4.1.1.4 Segmentation of liver tumor

4.1.1.5 Identification of Stages

4.1.1.1 DATA PREPROCESSING

The data processing module in the proposed system is a critical component that facilitates the transformation and analysis of input liver images. Initiating the data processing, the module conducts thorough data validation and quality checks, ensuring compliance with required specifications. Preprocessing techniques, such as normalization and resizing, enhance image quality for subsequent analysis. Integrated with the trained TransUNet model, the module transforms the preprocessed images into a format suitable for semantic segmentation. The model performs accurate tumor segmentation, extracting detailed boundaries for precise localization within the liver. Following segmentation, the module calculates tumor sizes, which are then employed to determine tumor stages based on predefined criteria. However, performing these steps effectively is critical for obtaining accurate and reliable results from machine learning models or data analysis. In image processing, preprocessing techniques are used to enhance images, remove noise, correct distortions, and standardize images for further analysis or computer vision applications. Operations like filtering, resizing, and color normalization are commonly employed.The processed data, including segmented tumor details and staging classifications, is presented through the web interface, empowering healthcare professionals with valuable insights for informed decision-making in the diagnosis and management of liver tumors.

4.1.1.2. TRANSUNET MODEL

Once after the data is uploaded and the preprocessing steps are done, the image will be suitable for testing to go to the trained model. Model training is a crucial phase in machine learning where a model learns patterns, relationships, and representations from the provided data. It involves exposing the model to a dataset (training data) to adjust its parameters or internal weights, allowing it to make predictions or perform tasks accurately on new, unseen data. The TransUNet model module in the proposed system is a key component responsible for accurate and detailed segmentation of liver tumors within medical images. Leveraging the TransUNet architecture, known for its effectiveness in semantic segmentation tasks, this module is crucial for learning intricate patterns and features associated with liver tumors. The TransUNet model has been trained on datasets of liver tumors, allowing it to generalize its knowledge and enhance segmentation accuracy. The module begins by receiving preprocessed liver images from the data processing module, ensuring that the input is standardized and optimized for segmentation. The TransUNet model employs attention mechanisms, which enable it to focus on relevant regions of the input images, contributing to improved segmentation precision. As the model performs semantic segmentation, it effectively distinguishes between tumor and non-tumor regions within the liver images. The resulting segmented tumors provide a comprehensive representation of their spatial distribution and shape, enabling precise localization. This information is critical for subsequent steps, including size calculation and staging. The integration of the TransUNet model module ensures that the system benefits from advanced deep learning capabilities, enhancing its ability to handle the complex and varied patterns of liver tumors. Training the model is a vital process. The model should be trained with various data and with variations in images to make the model understand the different aspects and show all the possibilities and other variations. Depending on the training model and training data, depends the segmentation output and the performance after. Hence training the model with appropriate and sufficient data is very vital.

4.1.1.3. FEATURE EXTRACTION:

The feature extraction module in this project is central to the accurate segmentation of liver tumors, employing the advanced architecture of the TransUNet model. This module extracts hierarchical features from preprocessed liver images. Leveraging transfer learning, the model has been trained on datasets of liver tumors, enhancing its ability to generalize intricate patterns. Through semantic segmentation, the module categorizes each pixel in the images as tumor resulting in a detailed segmentation map. The attention mechanisms allow the model to selectively focus on relevant regions, improving its capability to capture complex tumor variations. By representing both global and local patterns, the hierarchical features ensure adaptability to diverse tumor characteristics. Ultimately, the optimized representation generated by the feature extraction module forms the basis for precise tumor segmentation, contributing to the system's ability to provide detailed insights for improved diagnosis and treatment planning.

4.1.1.4 .SEGMENTATION OF LIVER TUMOR

The segmentation of liver tumor module is a critical component of the project, utilizing the advanced TransUNet model for accurate and detailed delineation of liver tumors within medical images. Taking the optimized image representation from the feature extraction module as input, this module employs the TransUNet model's semantic segmentation capabilities to classify each pixel in the image as tumor or non-tumor, generating a high-resolution segmentation map. The model excels at precisely delineating tumor boundaries, capturing intricate patterns and variations associated with liver tumors. The pixel-level classification and adaptive nature of the TransUNet model contribute to its effectiveness in handling varied tumor characteristics. The resulting segmented tumor boundaries serve as a foundational output for subsequent analyses, providing healthcare professionals with granular insights into the spatial distribution and extent of liver tumors, ultimately enhancing the system's diagnostic capabilities and supporting informed treatment decisions.

4.1.1.5. IDENTIFICATION OF STAGES

The identification of stages module is a critical component in the project, responsible for automating the staging classification of liver tumors based on their segmented sizes. Following the calculation of tumor sizes derived from the segmentation module, this module defines staging criteria aligned with clinical guidelines. By automating the staging process, tumors are categorized into different stages, providing healthcare professionals with valuable insights into the severity and progression of liver tumors. The module's integration with clinical standards ensures the relevance of the staging classifications, and the results are presented through a user-friendly web interface, facilitating easy interpretation by healthcare professionals. This automated staging not only streamlines the diagnostic workflow but also serves as a comprehensive clinical decision support tool, aiding in the formulation of informed treatment plans and interventions based on the identified stages of liver tumors.

The above modules would have explained the process of how the system is about to work and explains the process involved with it. The proper usage of modules reflects with the effective usage of model and effective solution in identifying the Liver tumor and stage of tumor.

CHAPTER 5

RESULTS AND DISCUSSION

Deep learning algorithms are a class of machine learning techniques inspired by the structure and function of the human brain's neural networks. These algorithms use multiple layers of interconnected nodes (neurons) to automatically learn representations of data from raw inputs. Once the tumor images are obtained, the process of preprocessing occurs in the transunet model. It Collect and preprocess a dataset of liver scans with tumor annotations. Preprocessing involves resizing images, normalizing intensity values, and possibly augmenting the dataset with transformations like rotations and flips.

Split the dataset into training, validation, and test sets. Train the selected model using the training data, optimizing for loss functions like Dice Loss or Cross-Entropy Loss. Fine-tune hyperparameters and monitor performance on the validation set to prevent overfitting. Once the features are obtained and the necessary images are segmented, further processing of image segmentation is done in order to show the stage of the liver tumor. Once the image successfully completes the preprocessing steps and have attained the necessary scans for the segmentation part, the work truly comes handy and the trained model effectively comes helpful in segmenting the tumor images.

The solution also mainly focuses on the stage depiction of the liver tumor which is done once the tumors are segmented from the provided scans. In order to obtain the required clear scan image of the tumor all the preprocessing steps and the segmentation parts plays a vital role. Once the Size is calculated the stage of the tumor will be depicted to the user in the web browser for user convenience. In this way deep learning effectively helps in segmentation of image and is predominantly helpful in the biomedical segmentation.

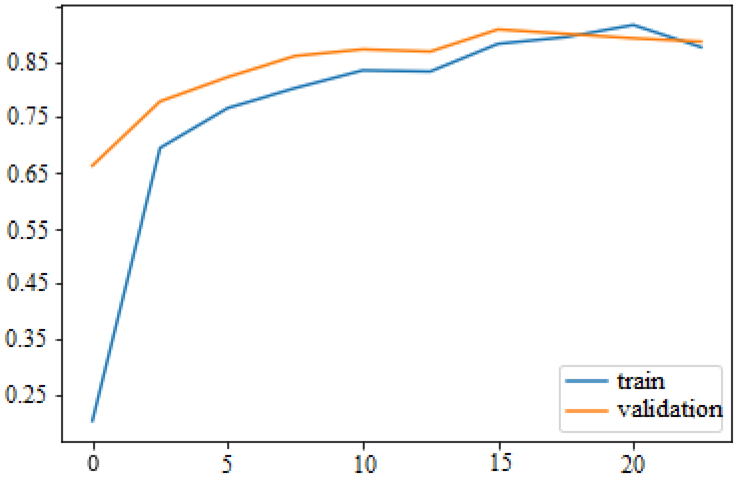

Fig 5.1 Accuracy Graph

The accuracy graph shows the training and testing sets provided for the model and the model has provided with around 85% accuracy and training has been done around for 10000 images and the testing and validation has been done to verify the obtained results and providing with certain accuracy.

TransUNet is a deep learning architecture that combines the strengths of both Transformer and UNet architectures for image segmentation tasks. It was proposed as a way to address limitations in both traditional convolutional neural networks (CNNs) like UNet and pure Transformer-based models. Self-attention mechanisms in the Transformer encoder enable the model to attend to different parts of the input image selectively, depending on their relevance to the segmentation task. This helps in capturing complex spatial relationships and improving the model's segmentation performance.

TransUNet is trained using standard supervised learning techniques, where the model is optimized to minimize a segmentation loss function, such as Dice Loss or Cross-Entropy Loss. The model parameters are updated using gradient descent-based optimization algorithms like Adam or SGD. ransUNet can be applied to various medical image segmentation tasks, including but not limited to, brain tumor segmentation, organ segmentation, lesion detection, and more. Its ability to capture global context information while maintaining spatial details makes it particularly suitable for analyzing complex medical images.

5.1 OUTPUT SCREENSHOTS

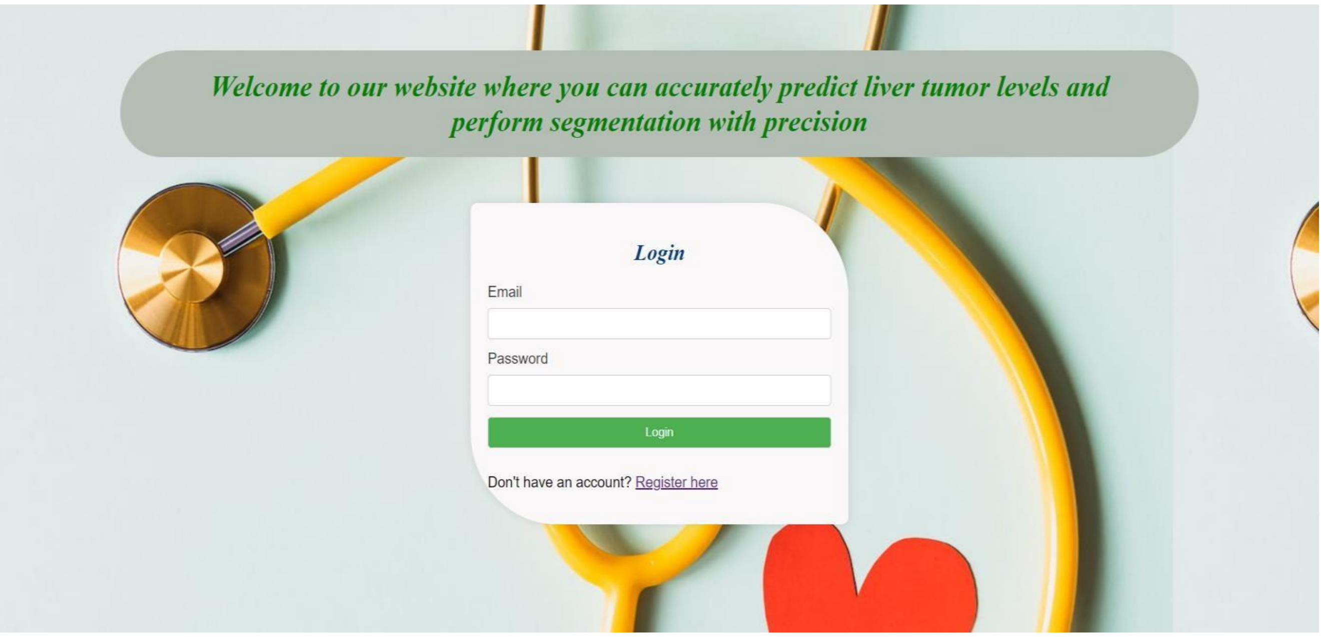

Fig 5.2 Home Page

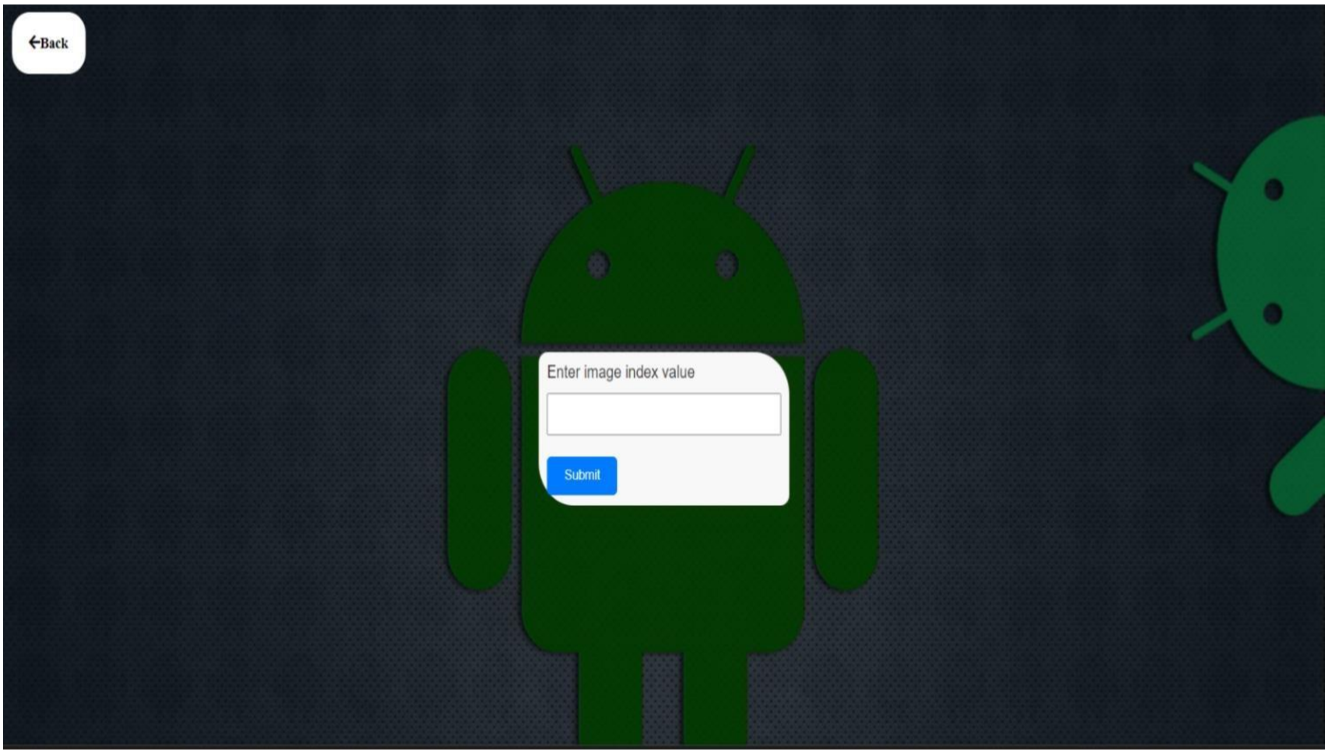

Fig 5.3 Number Epoch Input

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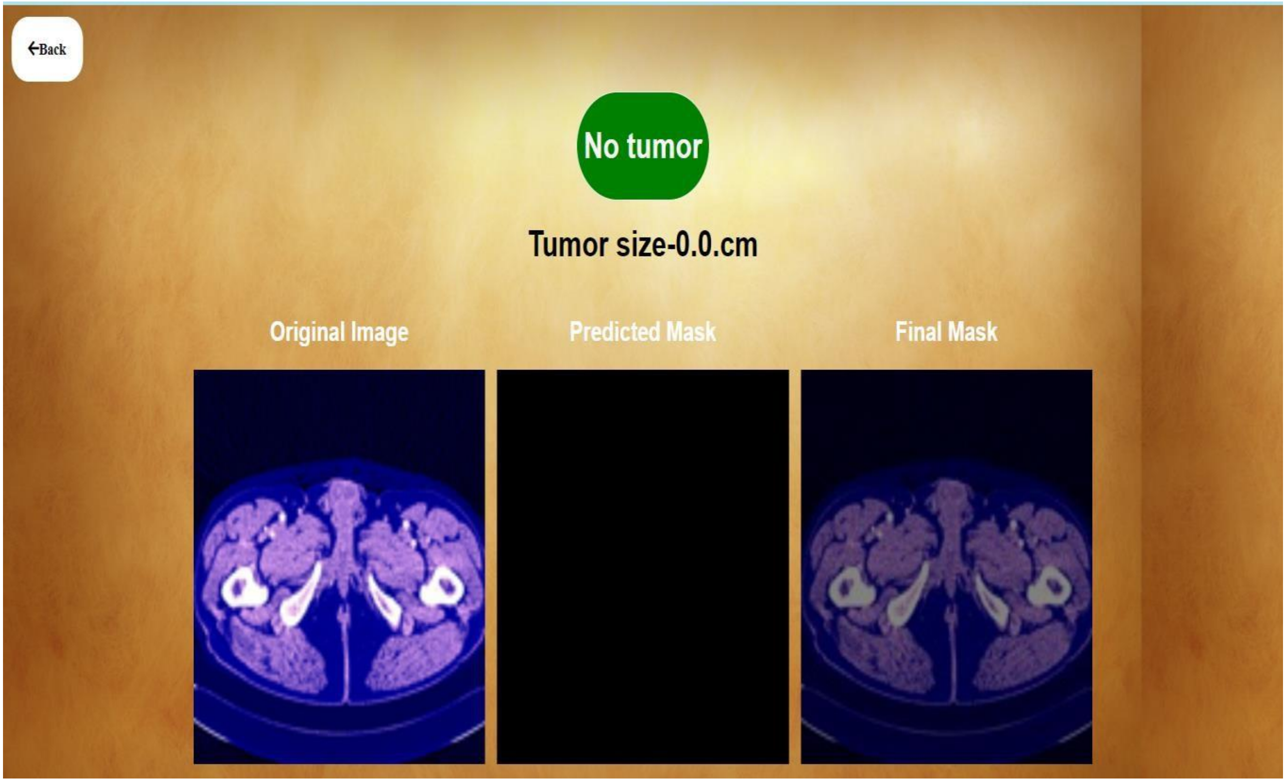

Fig 5.4 No tumor

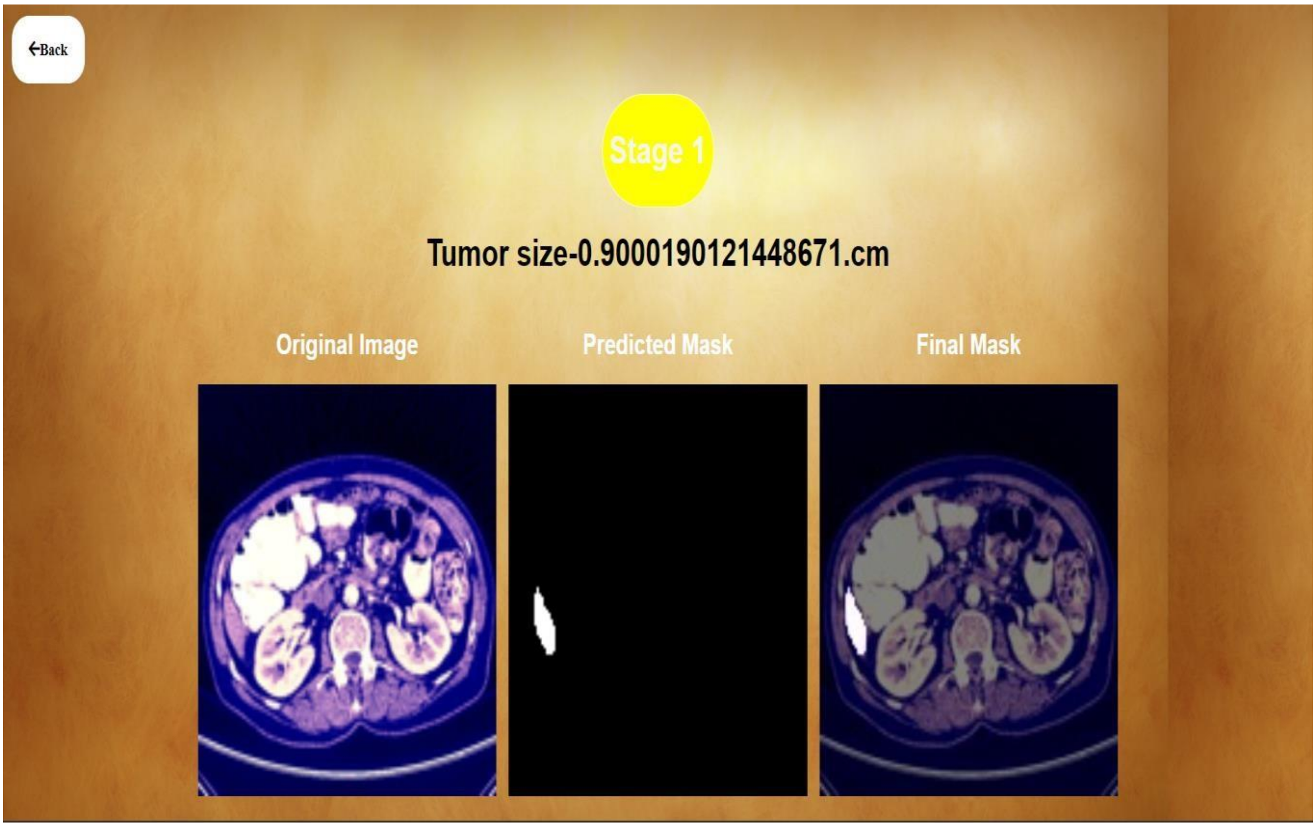

Fig 5.5 Stage 1 tumor

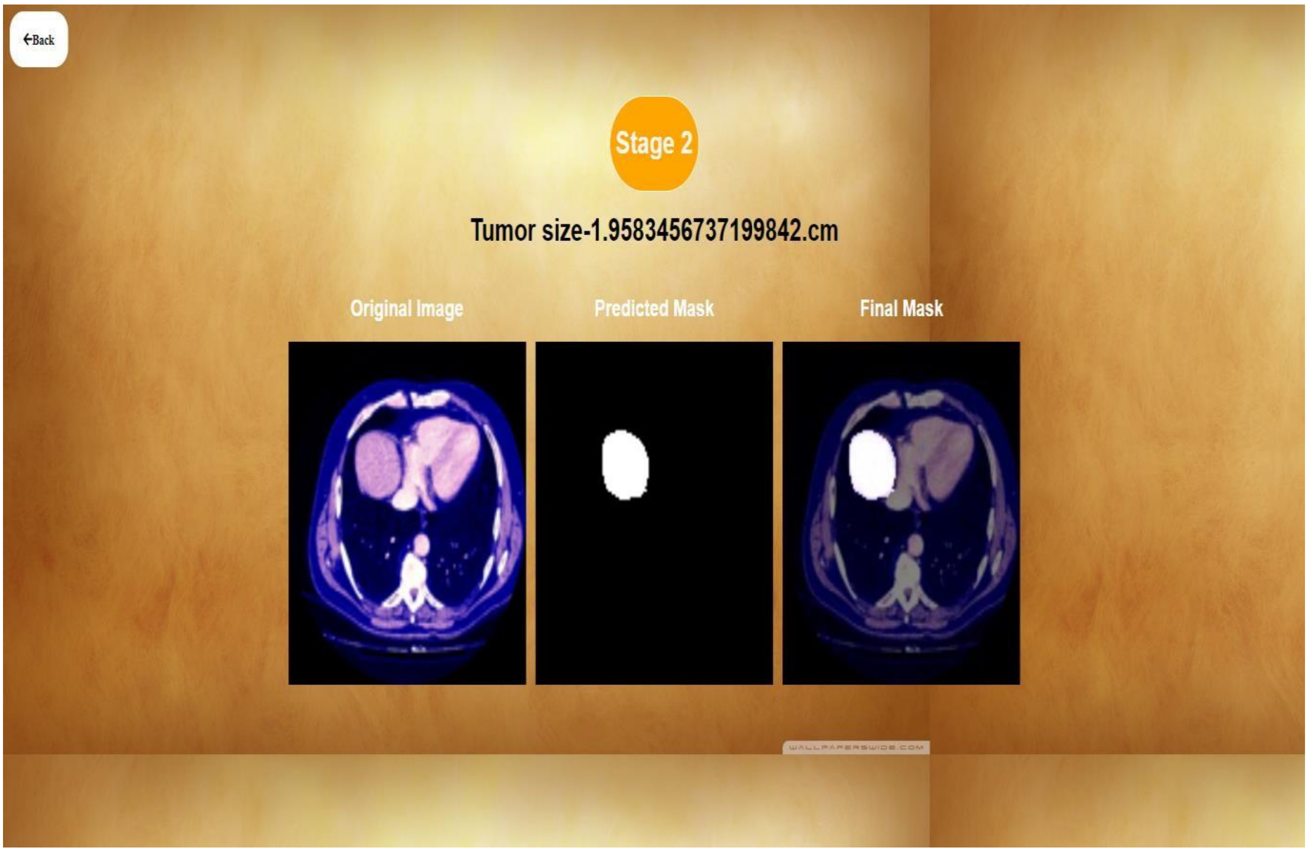

Fig 5.6 Stage 2 tumor

Fig 5.7 Stage 3 Tumor

CHAPTER 6
CONCLUSIONS AND FUTURE WORK

6.1.CONCLUSIONS

The project presents the user with the tumors from the CT scans that they have and instead of having the doctors having manually segmenting the tumors and it's also prone to various human errors, this segmentation of tumor in liver system helps everyone to analyze the severity and the tumor details for both the doctors and the users and gives a basic idea for the given scan. Once the image successfully completes the preprocessing steps and have attained the necessary scans for the segmentation part, the work truly comes handy and the trained model effectively comes helpful in segmenting the tumor images. The solution also mainly focuses on the stage depiction of the liver tumor which is done once the tumors are segmented from the provided scans. In order to obtain the required clear scan image of the tumor all the preprocessing steps and the segmentation parts plays a vital role. Once the Size is calculated the stage of the tumor will be depicted to the user in the web browser for user convenience. In this way deep learning effectively helps in segmentation of image and is predominantly helpful in the biomedical segmentation.

6.2 FUTURE ENHANCEMENT

Currently all the modules mentioned have been implemented and with an accuracy of specified levels has been testified. But in the field of medical sciences there is always development for more technological advancements in all sorts of ways. Currently we have used only the TransUNet model for effective image segmentation process. But with more further research and more combined alogirthms with more effective training and testing methods, the accuracy of the segmentation process will be far more improved and the process will be considered much more faster than the current ones. Also with the more amount of availability of similar Liver tumor images helps in intense training for the segmentation model to get adapted and be trained for further segmentation. Implement an active learning framework to intelligently select informative unlabeled samples for manual annotation, thereby reducing the annotation burden. Use uncertainty estimation techniques or query strategies to prioritize samples that are most beneficial for improving model performance. Integrate the liver tumor segmentation model into a clinical decision support system to assist radiologists and clinicians in diagnosis and treatment planning. Provide quantitative metrics (e.g., tumor volume, growth rate) and visualizations to aid

APPENDIX

CO-PO Mapping

PROJECT WORK COURSE OUTCOME (COs):

CO1: On completion it will make a major impact in polyp cancer detection and provide the fastest results for the given kvasir-seg image data.
CO2: It is an easy task for doctors for detecting, finding the polyp and showing the area of the polyp in a given image data.
CO3: This kind of project will have a huge impact in the medical field especially for detecting or finding the cancer cell because nowadays cancer has become a huge factor and most of the people were affected.
CO4: It motivates the students to develop these kinds of medical related projects so that they also could be a part of saving someone's life.
CO5: Students will be able to publish or release the project to society.

PROGRAM OUTCOMES (POs)

PO1: Engineering Knowledge: Apply the knowledge of engineering fundamentals, mathematics, science and technology and an engineering specialization to the solution of complex engineering problems.
PO2: Problem analysis: Ability to apply deep learning methodologies to solve computational tasks, model real world problems using appropriate datasets and suitable deep learning models. To understand standard practices and strategies in software project development using open-ended programming environments to deliver a quality product.
PO3: Design/development of solutions: Design solution for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety.

PO4: Conduct investigations of complex problems: Use research – based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis 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 modeling to complex engineering activities with an understanding of the limitations.

PO6: The Engineer and society: Apply reasoning informed by the contextual knowledge to assess social, health and safety 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 context, 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 practices.

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.

PROGRAM SPECIFIC OUTCOMES (PSOs):

PSO1: Foundation Skills: Ability to understand, analyze and develop computer programs in the areas related to algorithms, system software, web design, deep learning and cloud computing for efficient design of computer-based systems of varying complexity. Familiarity and practical competence with a broad range of programming languages and open-source platforms.

PSO2: Problem-solving Skills: Ability to apply mathematical methodologies to solve computational tasks, model real world problems using appropriate data structure and suitable algorithms. To understand standard practices and strategies in software project development using open-ended programming environments to deliver a quality product.

PSO3: Successful Progression: Ability to apply knowledge in various domains to identify research gaps and to provide solutions to new ideas, inculcate passion towards higher studies, creating innovative career paths to be an entrepreneur and evolving as an ethically responsible computer science professional.

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PHASE I

The paper titled “AUTOMATIC SEGMENTATION AND CATEGORIZATION OF LIVER TUMORS IN CT SCANS: A BIBLIOMETRIC ANALYSIS” authored by Dr.B. Vijayalakshmi, Subrahmanyan D and Jobin John Abraham was submitted to the 2024 International Conference on Innovation in Technology(INOCONF-24) presented in March 2024.

TITLE: AUTOMATIC SEGMENTATION AND CATEGORIZATION OF LIVER

TUMORS IN CT SCANS: A BIBLIOMETRIC ANALYSIS

AUTHORS: Dr.B. Vijayalakshmi,Subrahmanyan D and Jobin John Abraham

CONFERENCE: INOCONF-24 International Conference on Innovation in Technology
MODE OF PUBLICATION: ONLINE

STATUS: Presented and Accepted for publication

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AUTOMATIC SEGMENTATION AND CATEGORIZATION OF LIVER TUMORS IN CT SCANS: A BIBLIOMETRIC ANALYSIS

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***Abstract*—Liver tumors rank as the third deadliest cancer globally and the sixth most prevalent disease worldwide. They primarily afflict individuals who frequently consume tobacco or alcohol. Approximately 75-85 percent of primary liver cancer cases are attributed to these factors. However, manually diagnosing liver tumors presents significant challenges due to tumor heterogeneity, varying shapes and sizes, imaging artifacts, and limited annotated data. The critical task of segmenting liver tumors in medical images greatly impacts diagnosis and treatment planning. Numerous techniques and frameworks have been formulated for the early identification of tumors, improvingaccuracy, and aiding doctors in understanding tumor characteristics such as size and volume. Nevertheless, this process is error- prone and cumbersome. To address these challenges, a proper model is needed to identify the tumor and used for real-time image processing. This paper motivates to develop a system and assists doctors in swiftly identifying and segmenting tumors from images, providing an approximation of tumor size and stage for more precise treatment. Manual diagnosis is challenging, but advanced DL methods like TransUNet help with early detection and tumor segmentation, assisting doctors in providing timely and accurate treatment.**

***Keywords*—Deep Learning, Liver Tumor, Convolutional Neural Network.**

I. Introduction

Undiagnosed liver tumors lead to various problems and are considered to be fatal. The tumor gradually extends throughout the liver's regions and starts damaging the intestines and turning it into a huge havoc. The early identification of tumor, treatment and patient care of liver cancer is a serious worldwide health problem which presents substantial difficulties. Effective treatment planning and prognosis assessment depends on the precisesegmentation and delineation of liver tumors using medical imaging data. In order to help doctors evaluate the features, size, form, and therapeutic response of liver tumors, livertumor segmentation entails the exact delineation of tumor borders. Advanced techniques such as CT imaging, Ultrasound, MRI s cans and Positron Emission Tomography (PET) are commonly employed to detect liver tumors at preliminary phases to provide appropriate treatment and solve the issue. These scans provide the idea about the developing stage of the tumor to the doctor at earlier and help them to diagnose the disease by segmenting the tumor parts.

Manual segmentation requires more time and need expertise in the specific matter to identify the tumor. Here deep learning plays a major part involved with the Trans U-Net model for imaging and segmentation. Over the years many segmentation techniques have been developed with various models from Machine Learning and Advanced Neural Networks using various features such as volume and severity etc.

The system here focuses on determining the size of the tumor that's been present and displays the result with the possible stage category of tumor and cites the respective liver segmented details in order to help the doctors for a better understanding. The model clearly helps in finding the tumor from image by going through all parts. The system works well with a front end (User Interface) and when the user uploads the tumor images the CNN in the back end obtains the input and segments the liver and tumors for a clear segmentation. When the segmented results are obtained and when the model finds the tumor to be benign, the information will be displayed as not dangerous, yet doctor advice is recommended and when the tumor is confirmed while segmentation the interface displays the size of the tumor and along with which stage does it belong to, to indicate the user about the impending danger that user is going to face with.

II. Literature Survey

A.P R et al.[1] introduced a deep learning-based automated system for the detection of liver tumors. This system integrates segmentation, where liver and tumors are isolated from surrounding tissues, followed by a classification mechanism to differentiate benign from malignant tumors. Employing a dataset possibly consisting of MRI/CT scans, the research underscores the enhanced diagnostic accuracy of deep learning models over traditional methods. Addressing challenges such as tumor heterogeneity and variations in appearance, the authors optimized their models, showcasing the transformative potential of deep learning in the early detection and treatment of liver tumors.

A. R et al.[2] discussed about the Convolutional Neural Network (CNN) models and deep learning algorithms to detect the liver tumor. Highlighting the significance of accurate liver cancer detection methods, their research emphasizes the potential of CNNs in enhancing diagnostic precision. It utilizing a dataset, potentially of liver imaging scans, the study contrasts the capabilities of deep learning algorithms with traditional diagnostic techniques. The authors address challenges inherent to medical imaging, such as variations in tumor presentation, offering potential solutions through optimized deep learning models. This research underscores the pivotal role of advanced deep learning techniques, particularly CNNs, in revolutionizing liver cancer diagnostics.

Krishnakumari et al.[3] emphasized the importance of precise segmentation at the early stage to detect and treatment of liver tumors for depth analysis of liver tumor segmentation leveraging the capabilities of Deep ResUNet. Drawing upon a relevant dataset, possibly comprising liver imaging scans, the authors showcase the advantages of employing Deep ResUNet, a fusion of Residual Networks and U-Net architectures, over conventional segmentation methods. Through their results, the study underscores the efficacy and potential of the Deep ResUNet architecture in advancing medical imaging and offers significant insights to detect the liver tumor. .

A. M. et al.[4] delved into the realm of segmentation and identification of liver tumors through the deep learning. The paper highlights that precision and efficiency of liver tumor diagnosis is improved with deep learning techniques. Leveraging a possibly extensive dataset of liver imaging scans, the authors compared the efficacy of their proposed deep learning-based techniques with existing conventional methods. Addressing potential challenges in tumor variability and imaging inconsistencies, the team showcased the optimized capabilities of their deep learning approach. This research illustrates the advancementsin liver tumor diagnostics using advanced computational methods, emphasizing the transformative potential of deeplearning in medical imaging.

Munipraveena Rela et. al.[5] rigorously evaluated the performance of liver tumor classification employing machine learning algorithms. Delving deep into the challenges and intricacies of liver tumor diagnostics, it highlights the transformative prospective of machine learning in enhancing diagnostic accuracy and efficiency. By leveraging a potential dataset of liver imaging or related data, the authors systematically compared the performance metrics of various machine learning algorithms against conventional diagnostic methods. Throughout their research, challenges inherent to liver tumor variability and classification intricacies are addressed, leading to optimized machine learning methodologies. This work underscores the advancements and the critical role machine learning plays in liver tumor diagnostics, providing both a comprehensive evaluation and promising directions for thefuture.

Z. Naaqvi et al.[6] focused on Deep Convolutional Neural Networks (DCNN) to detection the tumor for liver cancer using Computed Tomography (CT) images. The study accentuates the transformative potential of DCNNs in enhancing the precision and robustness for diagnosing liver cancer using CT scans. Harnessing a relevant dataset, a comparative assessment betweenthe DCNN-based approach and existing diagnostic methodologies are discussed. They address challenges related to the nuances of CT imaging, such as variations in tumor presentation and contrast, and emphasize the advantages of using deep learning. This research not only showcases the benefits of applying advanced neural network architectures in medical imaging and also provides key predictions regarding the advancement of diagnostic techniques for liver cancer. in the age of deep learning.

Y. Li et al.[7] introduced a Global Normalized CAM with Dual CNN-Transformer called Sketch-supervised Histopathology Tumor Segmentation;. This research emphasizes the integration of Convolutional Neural Networks (CNN) and Transformer architectures,combined with a Global Normalised Class Activation Mapping (CAM) for enhanced segmentation performance. The ”sketch-supervised” technique, as suggested by the title, likely incorporates prior knowledge or guidance in the segmentation process, potentially leading to better localization and delineation of tumors in histopathological slides. The dual architecture emphasizes the synergy between CNNs, which excel at spatial hierarchies, and Transformers, which capture long-range dependencies, offering a robust method for accurate tumor segmentation. This study sets a precedent for future research in histopathological analysis.

A. Patel et al.[8] accentuated the strength of integrating W-Net, a potentially modified version or an extension of the U-Net architecture, with residual blocks, which are known to facilitate deeper network training by mitigating the vanishing gradient problem. This combination allows enhancing the accuracy and efficiency of liver segmentation tasks. By using a relevant dataset, likely consisting of medical imaging scans, the authors demonstrate that their proposed architecture performs better than traditional and existing segmentation methods. The integration of residual blocks within the W-Net framework is highlighted as a significant advancement, potentially leading to better feature extraction and improved segmentation outcomes. It provides a vital role in the fieldof medical imaging, particularly liver segmentation, and suggests a promising direction for future investigations in deep learning-based healthcare applications.

V. Gavini et al.[9] introduced an advanced model that synergistically integrates Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) networks for efficient result. The integration aims to capture both spatial features from images using CNN and sequential or temporal dependencies using LSTM, ensuring an enriched feature set for accurate liver tumor grading. The research work focus on a correlated feature set, indicating the importance of inter-feature relationshipsfor better classification results. The study showcases the efficacy of this integrated model over traditional methods by leveraging a comprehensive dataset of liver CT images. The results highlight the potential of combining CNN with LSTM in harnessing the intricacies of liver tumor grades, setting a new standard in medical imaging diagnostics for liver tumors.

Mr. Napte et al.[10] mapped the academic landscape, identifying major contributors, seminal papers, and prevailing trends in the domain. The bibliometric survey serves as a consolidated guide, presenting insights into the progress, challenges, and future directions in the realm of DCNN-based liver segmentation and cancer detection. Such an analysis is invaluable for researchers and practitioners in the field, offering a structured overview of existing literature, highlighting knowledge gaps, and suggesting potential avenues for future exploration in the domain of medical imaging and liver diagnostics.

L. Hong et al.[11] introduced an innovative model named "Qau-Net: Quartet Attention U-Net for Liver and Liver-Tumor Segmentation". The Qau-Net leverages a unique Quartet Attention mechanism to focus on salient features in the process of segmenting tumor. This mechanism improves the model'spotentially to distinguish between liver tissues and tumors with better accuracy results. The integration of this attention mechanism with the established U-Net architecture is particularly noteworthy, as it aims to elevate the performance analysis of segmentation for both liver and liver-tumor regions in medical imaging data. The study through empirical results describes the effectiveness of the Qau-Net and signifying a promising advancement in the realm of liver-related medical image analysis.

Vidhya Cardozo[12] developed a U-Net based network for segmentation of liver tumor and radiotherapy treatment. This research used a dataset with 52 patient CT axial scans with primary liver tumors. This process also included preprocessing steps which includes the HU windowing process to isolate livers and create masks for liver and tumor respectively. The images were split into 1400 for training and 600 for testing. This research utilized two fully convolutional neural networks with a U-Net segmentation. These networks segment tumors from the liver effectively.

M. Sato et al.[13] represented a 3D MTANN model that combines with a Hessian-based enhancer for segmentation of liver tumor. It highlights the advantages of this approach in terms of accuracy and efficiency, though it acknowledges the need for further validation on larger datasets and comparison with other segmentation methods.

S. T. Tran et al.[14] used the model U-Net model and Un- Net model where the images are segmented properly using appropriate features and considerably performing better with better attributes than other metrics using other models and usage of these models have proven to be better than previouslyused models.

Z. Khan et al.[15] introduced a AutoLiv algorithm to detect the tumor in the liver. It focuses on the potential of early diagnosis and reduced resource usage through automated detection techniques. Although it references employing deep learning and image analysis techniques, specific details about the algorithm's architecture and performancemetrics are not provided.

M. Rela et al.[16] used Multigabor Feature and non local active contours. The feature map isused for texture analysis and edge detection primarily fortumor detection. This feature map to set of array of gabor filters applied to image to extract the necessary features under various perspectives. Usage of non local active contoursleads to a more robust and accurate segmentation of objects in images and provides a clear boundary and differentiation between the liver lesions and tumor lesions. With using the given model, the performance is considered to be better than other previous models.

Dong et al.[17] proposed Hybridized Fully Convolutional Neural Networks (HFCNN) for liver cancer detection. It emphasizes the high accuracy achieved by combining different convolutional neural network architectures. The model demonstrates its effectiveness in classifying liver cancer and non-liver cancer cases, contributing to improved diagnosis accuracy.

X. Li et al.[18] discussed H-Dense UNet, a hybrid network for segmentation of liver and tumor. It highlights the incorporation of dense connections and a hybrid loss function to achieve the proposed method and enhanced state-of-art segmentation. The paper emphasizes the network's ability to handle challenging liver and tumor boundaries effectively.

Grzegorz Chlebus et al.[19] discussed a 2D fully convolutional neural network method with the post object processing step. The study involved the two working models such as voxel and object-level utilized for a calculated reduction of false findings. The specific objects are found and segmented and completely identifies the segmentedtumor with post processing.

B. Chen et al. [20] presented a semi-automatic method for segmentation of liver tumor based on nonlocal active contours and emphasized the algorithm's robustness. It addresses challenges related to tumor characteristics but suggests further research to enhance its accuracy and efficiency in tumor segmentation tasks.

Wen Li et al.[21] compared the performance of CNN model to various machine learning algorithms such as the Adaboost, Random Forests (RF) and Support Vector Machine (SVM) and the comparison in this research has showed a better performance than other machine learning algorithms. This research used the dataset of 30 portal phase enhanced CT images and its performance is compared with various features such as mean and variance and other vital features.

Daniels Pescia et al.[22] used the Statistical Shape Model (SSM). This method defines various normalization parameters to analyze the input and select the appropriate features required for segmentation and thefinal process of validation of the features and input images. The validation and training set images are given in the normalization stage for feature recognition and appropriate classifiers and validation mechanisms are implemented for enhancement of accuracy. The final qualifier determines whether the model and process is complete or not in the end.

Even though various strategies adapted for segmentation and classification of liver tumors were discussed, but it exhibits a few drawbacks:

Computational Complexity: H-DenseUNet[18] and the hybridized approach[19] are computationally complex and not suitable for real-time or resource-constrained environments.

- Sensitivity to Tumor Variability: Some methods struggle with low-contrast or heterogeneous tumors, which arecommon in clinical practice.
- Manual or Semi-Automatic Intervention: Certain approaches, like the semi-automatic method[15], require manual or semi-manual steps, which can be time-consuming and limit full automation in medical image analysis.

III Methods and Models Adapted:

A. Modified Dense U-Net

This architecture extends the basic capabilities of the U-Net by implementing new features such as dense connectivity, dilated convolutions, residual connections, attention mechanisms, and a few others. The primary goal of this model is to improve the network's performance and is mainly used for picture segmentation tasks by enhancing feature reuse, gradient flow, and the network's capacity to recognize features that are very specific. When comparing this model with the existing UNet architecture, this model has shown better performance in various researches than simply using the UNet model, achieving better accuracy and identifyingmore features.

B. W Net

WNet is an unsupervised image-to-image translation model consisting of two main stages: W-Net for segmentation and U- Net for translation. Initially, W-Net produces a soft segmentation map of the input image. This map, along with the originalimage, is then fed into U-Net to perform the translation. The training process is guided by a combination of reconstruction and segmentation-aware adversarial loss. A unique feature of WNet is its ability to operate without paired training examples. By segmenting the image first, it captures effective and minutedetails, providing effective translation without needing source- target image pairs.

C. U Net

This kind of architecture is commonly used in biomedical image analysis, because it performs segmentation tasks in an efficient manner. Its goal is to classify each pixel in an image based on certain category/. The U-Net architecture is symmetrical concerning the center, resembling a U-shape. Skip links connect the encoder and decoder routes, allowing for efficient feature reusethroughout the decoding process.

D. Active Contour Model

Active contour models, commonly known as ”snakes” are dynamic, deformable splines driven by both external and internal forces. They have been widely applied for image segmentation tasks, especially in medical imaging. Active contours are used to accurately delineate the tumor boundary within the liver. External forces are derived from the image data, ensuringthat the contour is attracted to features such as edges, which typically represent boundaries of tumors. Internal forces, on the other hand, maintain the contour's smoothness andregularity.

The contour iteratively evolves to minimize an energy function that encapsulates these forces. Challenges for using active contours in liver tumor segmentation include handling the presence of noise, heterogeneity of tumors, and complex liver morphology. However, when properly parameterized, they canprovide robust and accurate tumor delineations.

E. Statistical Shape Model

A statistical shape model is a mathematical representation used in image analysis and computer vision to capture the statistical variations in shapes of objects within a dataset. Shape analysis, shape matching, shape reconstruction, image segmentation, object identification, and deformable modeling in computer vision and medical image analysis are all potential applications for the statistical model.

F. Quartet Attention U-Net

This architecture involves various types of attentions such as temporal attention, spatial attention, channel attention and feature attention, etc. Attention mechanisms are commonly used here to provide relevant importance and provide value to the features obtained from the dataset. Effectively the structure has 4 phases such as encoder, Quartet attention module, decoder and output layer. The encoder extracts the features and reduces the dimensions from the dataset and the attention module adds appropriate weights to the obtained features in order to provide a better understanding to the algorithm. The decoder is used to analyse the features and combine them with the previously obtained low level features and for effective transformation. In the end, the output layer provides the segmented output with appropriate activation functions.

G. 3D U-Net

The 3D U-Net takes volumetric data as input and outputs volumetric predictions. In comparison, the 2D U-Net operates on 2D images and produces 2D segmentation. The 3D U-Net contracting route (encoder) consists of multiple layers with 3D convolutions followed by 3D pooling layers. The spatial dimensions of the input are gradually reduced while extracting features. The 3D U-Net uses skip connections to connect the relevant encoder and decoder levels. These connections allow the decoder to access feature maps from the encoder, enabling more accurate localization and segmentation of structures in the 3D volume.

H. TransUNet

Unlike the extended architectures of U-Net, TransUNet uniquely uses a hybrid structure of transformer and the U- Net architecture and provides an enhanced performance. While using the TransUNet there is a considerable loss of feature resolution due to the usage of transformers and this is effectively stopped by the usage of hybrid CNN transformer architecture. The encoding is used for feature extraction and is sent further to evaluate and provide the importance to respective features. The decoders obtain the results from segmented parts andanalyses the features.

IV COMPARISION AND DISCUSSION

As analyzed from the previous research papers and published results, most of the focus was on the accuracy and segmentation of tumors with better precision and enhanced accuracy. Most researchers used Convolutional Neural Net- work (CNN) and differed with U-Net, RES-Net, and various modified algorithms and other machine learning algorithms.

The comparative study and analysis of CT scan images for segmentation and classification is discussed in Table 1. This table effectively helps the user to understand the techniques from existing systems and helps to identify the model for other implementation of projects and this comparison is vital in order to check and compare the accuracy and implement models with better performance.

The complete study of segmentation of liver tumors using the Convolutional Neural Network (CNN) and TransUNet model is discussed in this paper. It motivates to develop a web application with an appropriate User Interface and an appropriate backend for the processing of Deep Learning models to segment the imaging datasets. The input data is analyzed and segmented into different layers as livers and liver tumors, and the severity of tumors is analyzed by checking various parameters such as volume, size, etc.

The segmentation analyzes and determines if the tumor is malignant or benign, and appropriate results are further implemented. When the images are segmented and analyzed properly, the newfactor of finding the size of the tumor is added to analyze stage of the tumor of the provided input. The tumor size is calculated with appropriate formulas and calculations, and depending upon the size obtained from the size calculation, the stage of the tumor, the user is intimated about the stage of the tumor that the user might possibly have, along with the other obtained results from segmentation and analytics.

CONCLUSION

In this study segmentation and categorization of liver tumor on CT scans with various research papers are analyzed. It provides an analysis of segmentation and enhances the researchers to do research related to medical image processing in future. It motivates to develop a model to perform segmentation of CT liver tumor to recognize the diseases and categorize it. This paper aims to identify proper model and method for liver tumor segmentation task and to clearly categorize the tumors for the input images.

Table 1: SUMMARY OF SEGMENTATION AND CLASSIFICATION OF CT LIVER TUMOR

Author	Algorithm	Dataset	Findings
Aparna P R, Libish T M [2023]	Modified Dense Unet architecture.	This research uses LiTS dataset contains 130 3D CT scansof patients and hepatic tumors in 75% of cases.	An accuracy of 92.60% and a dice score of 95.40% are achieved.
Yilong Li, Linyan Wang, Xingru Huang, Yaqi Wang†, Le Dong, Ruiquan Ge, Huiyu Zhou, Juan Ye, Qianni Zhang[2023]	sketch-supervised method, based on a dual CNN-Transformer network and a modified global normalised classactivation map.	This research Uses PAIP2019 dataset	The experimental research shows that 76.68% IOU and 86.69% dice scores is obtained on sketchbased segmentation
Munipraveena Rela, Suryakari Nagaraja Rao and Patil Ramana Reddy[2022]	Support Vector Machine (SVM), K - Nearest Neighbour (KNN), Naïve Bayes (NB), ENSEMBLETREE	68 CT images with 86 features are used in this research.	The accuracy 84.6%.is obtained for SVM method
Alok Patel,Kumar Prateek, Soumyadev Maity [2022]	W-Net architecture	This research uses LiTS dataset comprising 130 3D CT scans of patients with hepatic tumors in 75% of cases.	A dice score of 92.56% is achieved on tumor segmentation which is better than previously implied models.
Venkateswarlu Gavini, G.R. Jothi Lakshmi[2022]	Convolution Neural Network (CNN) based long short-term memory (LSTM) with correlated feature set (CNN- LSTM-CFS) model.	This research uses both datas from LiTS and 3D-IRCADB datasets	A 98% accuracy rate for the CNN based LSTM approach is obtained.
Luminzi Hong,Risheng Wang, Tao Lei, Xiaogang Du YongWan [2021]	novel network called quartet attention U-Net (QAU-Net)	This research uses MIC-CAI 2017 Liver Tumor Segmentation Challenge (LiTS) dataset	The proposed method designed a long-short skip connection to avoid duplicate resolution and improved accuracy.
Song –Toan Tran, Ching-Hwa Cheng, Don-Gey Liu [2021]	U^n-Net, an n-fold network architecture	This research uses two public datasets LiTS and 3DIRCADb	A dice similarity coefficient of 96.38% and 73.34% is achieve for liver and tumor segmentation
Munipraveena Rela , Na-garaja Rao Suryakari, P Ramana Reddy [2020]	The Gaussian Mixture Model (GMM)	This research uses LiTS dataset, 3DIRCADb dataset, Clinical dataset	The research work.is carried out an aid of optimal feature selection and classification models
Xin Dong, Yizhao Zhou, Lantian Wang, Jingfeng Peng, Yanbo Lou, Yiqun Fan[2019]	Hybridized Fully Convolutional Neural (HFCNN)	-	This article achieved a Dice coefficient of 0.92.
Xiaomeng Li, Hao Chen, Chi-Wing Fu[2018]	densely connected UNet (H-DenseUNet),	This research used MICCAI 2017 Liver Tumor Segmentation(LiTS) Challenge and 3DIRCADb Dataset.	This research achieved a Dice score of 98.2% and 93.7%.
Bin Chen Yang Chen , Guanyu Yang, Jingyu Meng,Rui Zeng,Limin Luo[2015]	Multigabor feature map and non local active con-tours	-	The mean OE and RDE obtained in the proposed system are 23.86% and 17.01% respectively.
Daniel Pescia[2011]	Statistical Shape Model(SSM)	MICCAI 2018 datasets	The mean OE and RDE with proposed system are 23.86% and 17.01% respectively.

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PHASE II

The paper titled " AUTOMATIC SEGMENTATION AND CATEGORIZATION OF LIVER TUMORS IN CT SCANS USING DEEP LEARNING" authored by Dr. B. Vijayalakshmi, Subrahmanyan D and Jobin John Abraham was submitted to ICAIS 4th International Conference on Artificial Intelligence and Smart Energy.

TITLE: AUTOMATIC SEGMENTATION AND CATEGORIZATION OF LIVER TUMORS IN CT SCANS USING DEEP LEARNING

AUTHOR: Dr. B. Vijayalakshmi,Subrahmanyan D and Jobin John Abraham

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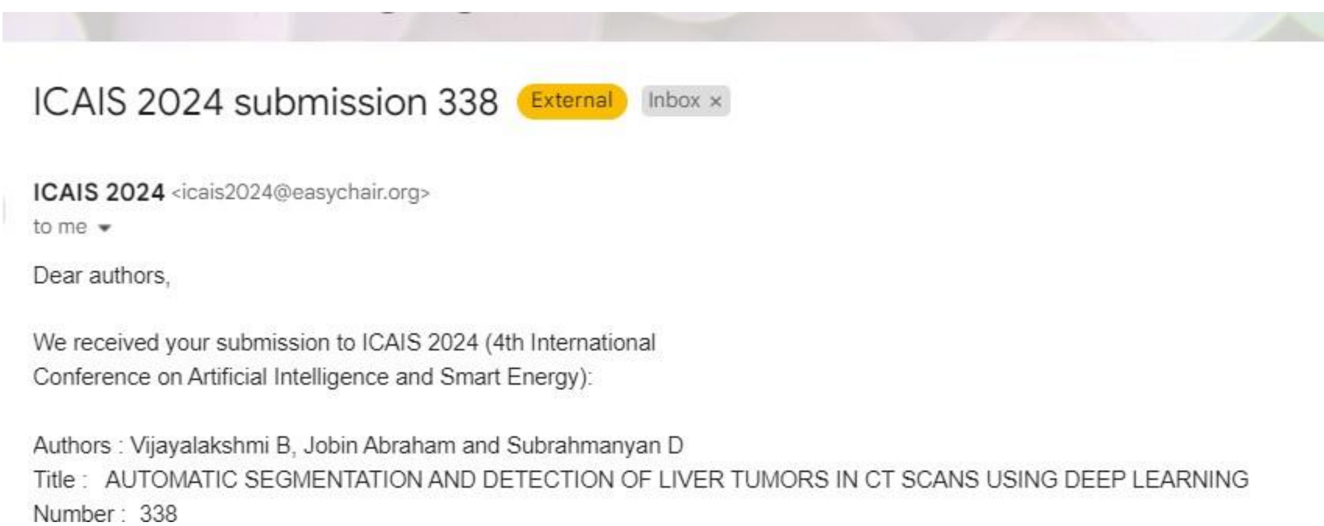

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AUTOMATIC SEGMENTATION AND DETECTION OF LIVER TUMORS IN CT SCANS USING DEEP LEARNING

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***Abstract*—Nowadays cancer disease leads to increase of death rate, so liver cancer is graded as third deadliest cancer throughout the world. Early detection of liver tumor is essential for effective treatment. However, manual diagnosis presents challenges due to tumor heterogeneity, variability in shape and size, and limited annotated data. This study addresses these challenges by developing a deep learning (DL) system for automated liver tumor segmentation and size estimation. Utilizing the TransUNet architecture, our system accurately segments tumors in medical images, facilitating diagnosis and treatment planning. By automating this critical task, errors are minimized, and the diagnostic process is expedited, enabling timely interventions. Additionally, the system provides estimates of tumor size, aiding in staging and treatment decisions. This paper represents a significant advancement in liver tumor detection, amalgamating robust DL techniques with clinical expertise to empower healthcare professionals in delivering more effective patient care, potentially saving lives.**

***Keywords*—Liver Tumor, Segmentation, TransUNet, Tumor Size Estimation and Deep Learning.**

I. Introduction

Liver cancer is most common disease which leads to death if a liver tumor is undiagnosed at earlier. The tumor is gradually enlarge around the region of liver and begins to damaging the intestines and turning it into a huge mess. There is a substantial difficulty for early identification of Liver tumor, treatment and patient care to increase their survival rate. Effective treatment and diagnosis assessment depends on the precisesegmentation and delineation of liver tumors using medical imaging data. In order to help doctors to evaluate the features, size, form and therapeutic response of liver tumors, liver tumor segmentation involves the exact delineation of tumor borders. Advanced medical imaging techniques such as CT imaging, Ultrasound, MRI s cans and Positron Emission Tomography (PET) are commonly employed to detect liver tumors at preliminary phases to provide appropriate treatment and solve the problem. These scans provide the idea about the developing stage of the tumor to the doctor at earlier and help them to diagnose the disease by segmenting the tumor parts.

As more advancement in the field of technology, Manual segmentation consume more time and required expertise in the specific matter to identify the tumor. In this research, deep learning plays a vital role involved with the Trans U-Net model for imaging and segmentation. Over the years many segmentation techniques have been developed with various models from Machine Learning and Advanced Neural Networks using various features such as volume and severity etc.

The system focuses on determining the size of the tumor that's present and displays the result with the possible stage category of tumor and cites the particular liver segmented details in order to help the doctors for a better understanding. The model clearly helps in finding the tumor at various stages. The front end (User Interface) is used for selecting the images and CNN in the back end to obtains the input and segments the liver and tumors for an automatic segmentation. When the segmented results are obtained and when the model finds the tumor to be benign, the information will be displayed as not dangerous, yet doctor advice is recommended and when the tumor is confirmed while segmentation the interface displays the size of the tumor and along with which stage does it belong to, to indicate the user about the impending danger that user is going to face with.

II. Literature Survey

A.P R et al.[1] developed a deep learning system for automated liver tumor detection, highlights the potential of deep learning to address tumor heterogeneity and variability, potentially transforming early detection and treatment. A. R et al.[2] investigated using CNNs and deep learning for liver tumor detection. Krishnakumari et al.[3] emphasized early and precise liver tumor segmentation using Deep ResUNet, a fusion of Residual Networks and U-Net. A. M. et al.[4] explored deep learning for liver tumor segmentation and identification. Their approach addressed tumor variability and image inconsistencies, showcasing the potential of deep learning to transform liver tumor diagnostics.

Munipraveena Rela et. al.[5] rigorously evaluated machine learning algorithms for liver tumor classification to improve accuracy and efficiency on CT Liver images. Z. Naaqvi et al.[6] utilized Deep Convolutional Neural Networks (DCNNs) for liver tumor detection in CT scans. Y. Li et al.[7] proposed a "Sketch-supervised Histopathology Tumor Segmentation" method using a Dual CNN-Transformer with Global Normalized CAM. This combines CNNs' spatial understanding with Transformers' long-range dependency learning, improving tumor segmentation accuracy in histopathological analysis. A. Patel et al.[8] proposed a liver segmentation method combining

W-Net (potentially a modified U-Net) with residual blocks.

V. Gavini et al.[9] proposed a CNN-LSTM model for accurate liver tumor grading. This combines CNNs' ability to capture spatial features from images with LSTMs' expertise in learning sequential and temporal dependencies. Napte et al.[10] conducted a bibliometric survey of Deep Convolutional Neural Network (DCNN) research in liver segmentation and cancer detection. L. Hong et al.[11] proposed Qau-Net, a novel U-Net based model using a "Quartet Attention" mechanism for liver-tumor segmentation. Their study suggests Qau-Net's effectiveness and potential for advancements in liver-related medical image analysis.

Vidhya Cardozo[12] developed a U-Net based network for liver tumor and radiotherapy segmentation on a dataset of 52 patient CT scans. Using HU windowing for pre-processing, the data was split into 1400 training and 600 testing images. Two fully convolutional neural networks within the U-Net architecture effectively segmented tumors from the liver. M. Sato et al.[13] proposed a 3D MTANN model with a Hessian-based enhancer for liver tumor segmentation. While showing promising accuracy and efficiency, they acknowledge the need for further validation on larger datasets and comparisons with other methods.

S. T. Tran et al.[14] compared U-Net and Un-Net models for liver segmentation, demonstrating their superior performance compared to other models based on appropriate feature selection and improved metrics. This suggests these models are a promising advancement over previous approaches. Z. Khan et al.[15] proposed the AutoLiv algorithm for automated liver tumor detection. M. Rela et al.[16] used Multigabor Features and non-local active contours for liver tumor segmentation. Their model reportedly shows better performance than previous approaches. Dong et al.[17] proposed a Hybridized Fully Convolutional Neural Network (HFCNN) for liver cancer detection.

X. Li et al.[18] proposed H-Dense UNet, a hybrid network combining dense connections and a custom loss function for liver and tumor segmentation. This method aims to achieve state-of-the-art performance, particularly in handling challenging boundaries between liver and tumor tissues. Grzegorz Chlebus et al.[19] proposed a 2D CNN with post-processing for liver tumor detection. Using two models (voxel-level and object-level), they achieved a reduction in false positives. The workflow involves object detection and segmentation, followed by post-processing for precise tumor identification. B. Chen et al. [20] proposed a semi-automatic liver tumor segmentation method using nonlocal active contours, highlighting its robustness against tumor variability. Wen Li et al.[21] compared a CNN model to machine learning algorithms (Adaboost, Random Forests, Support Vector Machine) for liver tumor detection using a dataset of 30 CT images.

III. Proposed Method

A deep learning based framework for accurate and segmentation of liver tumors in CT scans are discussed in this study. The experiment is executed in Python with Windows environment. The CT liver tumor images are collected from Kaggle (LiTS) Dataset, which is commonly available public dataset. The training images are 4010 and testing images are 1719 respectively.

The primary objective is to augment the database of CT images, a crucial requirement for training deep convolutional neural networks (DCNNs). Preprocessing steps involve enhancing CT images and eliminating unnecessary noise to refine the database and improve its utility. Through meticulous statistical evaluation of various CNN architectures, optimal performance is achieved in both liver and tumor segmentation, ensuring accurate results with minimal time and effort. This integrated approach, combining data augmentation, network architecture selection, and efficient segmentation, holds immense potential for advancing liver tumor detection and diagnosis in clinical settings. Finally classification is performed with Convolutional Neural Network (CNN) architecture known as TransUNet, excels in both tumor classification and segmentation.

A. System Design

The overarching objective of this model is to augment network performance, particularly tailored for image segmentation tasks. By enhancing feature reuse, optimizing gradient flow, and augmenting the network's capacity to discern highly specific features, this model represents a significant advancement in the field.

The system flow of Segmentation and classification of CT liver Tumor is depicted in Fig1. Each task within the system flow builds upon the inference of preceding tasks, establishing a cohesive relationship among the various components, as illustrated through the system's design.

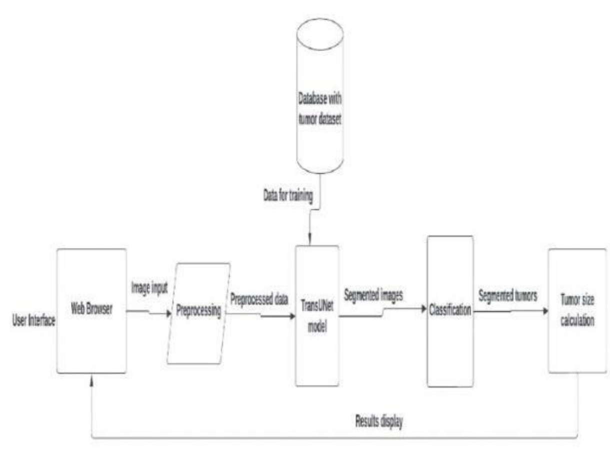


Fig 1: System flow of Segmentation and classification of CT liver Tumor

B. Implementation

Initially, the system interacts with users through a web interface to analyze submitted CT scan images. Initially the images are having a size of 512 × 512 measurement in the LITS dataset. It is always challenging task to have such 512 x

512 images due to limited CPU memory. Consequently, all images are resized having a size of 224 × 224 measurement and also normalization is applied on all the images and mask reshaping is also done. Advanced noise reduction techniques ensure clarity and precision by removing irrelevant artifacts, while adaptive contrast enhancement methods illuminate tumor regions for optimal visibility. This preprocessing ensures that the data fed into the TransUNet model, is refined and optimized for accurate segmentation.

The preprocessed data then enters the core of the system - the TransUNet model. This deep learning architecture, has been meticulously trained on a vast database of labeled liver images and corresponding tumor regions. Leveraging this extensive knowledge, the TransUNet model performs the critical task of segmentation with remarkable precision, isolating the liver and tumor regions from the image.

Subsequently, the system proceeds to characterize the segmented tumor regions. A classification algorithm, trained on labeled data, carefully analyzes these regions to determine whether the tumors are benign or malignant, providing crucial information for diagnosis and treatment planning. Furthermore, the system quantifies the extent of the identified tumors using advanced algorithms, to calculate tumor size with high accuracy. This quantitative information is essential for accurate diagnosis and guiding treatment decisions.

Finally, the comprehensive results of this meticulous analysis are presented to users through a user-friendly web interface. Segmented tumor regions overlaid on the original CT scan provide a visual representation of the findings. Additionally, calculated tumor size, classification results are clearly displayed, offering a comprehensive overview of the analysis.

Throughout this intricate process, the system relies on a comprehensive tumor dataset, providing the TransUNet model with the necessary knowledge and experience for accurate segmentation and classification. Continuous updates and incorporation of diverse data further enhance the system's robustness and adaptability to various patient populations. This integrated workflow represents a significant advancement in liver tumor analysis, empowering medical professionals with accurate, efficient, and insightful results, ultimately contributing to improved diagnostic outcomes and patient care.

C. TransUNet

Unlike the extended architectures of U-Net, TransUNet uniquely uses a hybrid structure of transformer and the U- Net architecture and provides an enhanced performance. While using the TransUNet there is a considerable loss of feature resolution due to the usage of transformers and this is effectively stopped by the usage of hybrid CNN transformer architecture. The encoding is used for feature extraction and is sent further to evaluate and provide the importance to respective features. The decoders obtain the results from segmented parts andanalyses the features.

IV RESULTS AND DISCUSSION

Most of the research shows that Convolutional Neural Network (CNN) and differed with U-Net, RES-Net, and various modified algorithms and other machine learning algorithms are used for segmentation and classification of liver images. The complete study of segmentation of liver tumors using the Convolutional Neural Network (CNN) and TransUNet model is discussed in this paper. It motivates to develop a web application with an appropriate User Interface and an appropriate backend for the processing of Deep Learning models to segment the imaging datasets. The input data is analyzed and segmented into different layers as livers and liver tumors, and the severity of tumors is analyzed by checking various parameters such as volume, size, etc.

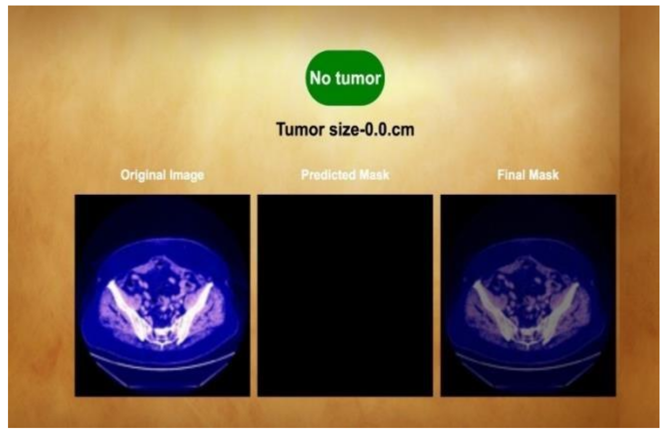
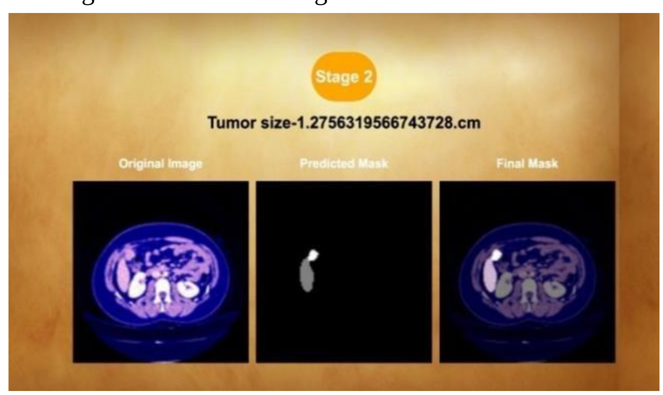
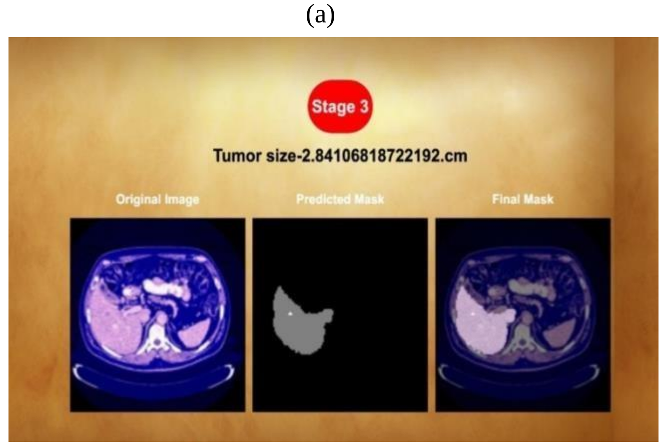


Fig2: Normal Liver image without Tumor



(a)



(b)

Fig3(a), (b) Tumor image with different Stages

The comparative analysis between various segmentation and classification of CT liver images are discussed in Table 1. The table reveals that an effective result is obtained using the proposed method. The segmentation analyzes and determines if the tumor is malignant or benign, and appropriate results are further implemented. When the images are segmented and analyzed properly, the newfactor of finding the size of the tumor is added to analyze stage of the tumor of the provided input. The tumor size is calculated with appropriate formulas and calculations, and depending upon the size obtained from the size calculation, the stage of the tumor is determiner. This system intimates the user about the liver without tumor and with tumor. The liver without tumor is shown in Fig2 and stage level of the tumor is shown in Fig3 (a) and (b) respectively. It helps to classify the images as either normal liver and malignant liver and analysis of classification results are calculated.

CONCLUSION

In this study segmentation and categorization of liver tumor on CT scans with deep learning is discussed. It motivates to develop a model to perform segmentation of CT liver tumor and categorize the CT scan liver images as Liver without tumor and tumor at stage 2 and stage 3 depending on its size. It provides an analysis of segmentation and enhances the researchers to do research related to medical image processing in future.

Table 1: COMPARATIVE ANALYSIS OF SEGMENTATION AND CLASSIFICATION OF CT LIVER TUMOR

Author	Algorithm	Dataset	Findings
Wen Li,, Fucang Jia, Qinmao Hu[2015]	Deep Convolutional Neural Networks	26 portal phase enhanced CT images	The average Dice Similarity Coefficient(DSC), Precision and Recall of 80.06%±1..63%, 82.67%±1.43 and 84.34%±1.61% is obtained respectively
Xiaomeng Li, Hao Chen, Chi-Wing Fu[2018]	densely connected UNet (H-DenseUNet),	MICCAI 2017 Liver Tumor Segmentation (LiTS) Challenge and 3DIRCADb Dataset.	Dice score of 98.2% and 93.7% is achieved.
Xin Dong, Yizhao Zhou, Lantian Wang, Jingfeng Peng, Yanbo Lou, Yiqun Fan[2019]	Hybridized Fully Neural Convolutional(HFCNN)	-	Dice coefficient of 92% is achieved.
Munipraveena Rela , Nagaraja Rao Suryakari, P Ramana Reddy [2020]	The Gaussian Mixture Model (GMM)	LiTS dataset, 3DIRCADb dataset, Clinical dataset	The research work.is carried out an aid of optimal feature selection and classification models
Song –Toan Tran, Ching-Hwa Cheng, Don-Gey Liu [2021]	U^n-Net, an n-fold network architecture	LiTS and3DIRCADb	A dice similarity coefficient of 96.38% and 73.34% is achieved for liver and tumor segmentation
Luminzi Hong,Risheng Wang, Tao Lei, Xiaogang Du YongWan [2021]	Novel network called quartet attention U-Net (QAU-Net)	MICCAI 2017 Liver Tumor Segmentation Challenge (LiTS) dataset	This is designed a long-short skip connection to avoid duplicate resolution and improved accuracy.
Venkateswarlu Gavini, G. R. Jothi Lakshmi [2022]	Convolution Neural Network (CNN) based long short-term memory (LSTM) with correlated feature set (CNN- LSTM-CFS) model.	LiTS and 3DIRCADB datasets	A 98% accuracy rate for the CNN based LSTM approach is obtained.
Alok Patel, Kumar Prateek, Soumyadev Maity [2022]	W-Net architecture	LiTS dataset comprising 130 3D CT scans with hepatic tumors.	A dice score of 92.56% is achieved
Munipraveena Rela, Suryakari Nagaraja Rao and Patil Ramana Reddy[2022]	Support Vector Machine (SVM),K-Nearest Neighbour (KNN), Naïve Bayes(NB) ENSEMBLETREE	68 CT images with 86 features	The accuracy 84.6%.is obtained for SVM method
Yilong Li, Linyan Wang, Xingru Huang, Yaqi Wang†, Le Dong, Ruiquan Ge, Huiyu Zhou, Juan Ye, QianniZhang[2023]	Sketch-supervised method, based on a dual CNN-Transformer network and a modified global normalised classactivation map.	PAIP2019 dataset	76.68% IOU and 86.69% dice scores is obtained on sketchbased segmentation
Aparna P R, Libish T M [2023]	Modified Dense Unet architecture.	LiTS dataset contains 130 3D CT scans of patients and hepatic tumors	An accuracy of 92.60% and a dice score of 95.40% are achieved.
Proposed Method	Deep Learning	LiTS dataset	It helps to classify tumor with its size and its stage level.

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