AI-Based liver abnormalities detection using medical images

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Abstract— **This paper introduces a deep-learning framework specifically designed for the accurate detection of hepatomegaly in CT images. This approach aims to address the limitations found in conventional imaging modalities and manual assessment methods. A meticulously curated and diverse dataset, including annotated CT scans of both normal and hepatomegaly-affected livers, is employed to support robust model training and optimization. Extensive fine-tuning of the model architecture and hyperparameters is conducted to enhance generalization across varied datasets and clinical scenarios. Ethical considerations are fundamental to this methodology, emphasizing transparency, fairness, and patient privacy throughout the model's development. Successful implementation of this framework is expected to significantly improve the efficiency of hepatomegaly detection in clinical settings, leading to better patient care. Additionally, the research highlights a commitment to advancing medical imaging technology while maintaining ethical standards and prioritizing patient welfare. The proposed deep-learning model's potential impact goes beyond hepatomegaly detection, with broader implications for the field of medical imaging and precision medicine. By revolutionizing diagnostic processes, this work aims to enhance healthcare outcomes and pave the way for future innovations in this critical area.**

***Index Terms*— Dice Similarity Coefficient (DSC), Convolutional Neural Networks (CNNs), Multiple Instance Learning (MIL),Computed Tomography (CT),**

I. INTRODUCTION

The idea revolves around leveraging advanced computer techniques, specifically deep learning, within the realm of medical imaging, with a keen focus on analyzing liver images obtained through CT scans. The primary objective is not just to identify the presence of the liver but to delve deeper into the nuances of its shapes and structures, comparing them against a healthy liver's standard characteristics. The fundamental purpose of this project is to detect deviations or irregularities in the liver's shape that might serve as early indicators of potential health risks or underlying conditions.

By harnessing cutting-edge algorithms and intricate medical images, the goal is to move beyond mere identification and toward a proactive approach to healthcare. The significance lies in the potential to revolutionize healthcare practices. Traditionally, medical imaging has been pivotal in diagnosis, yet this project aims to push boundaries further by enabling the detection of subtle abnormalities that might escape conventional diagnostics. By pinpointing these deviations early on, there's an opportunity to predict and prevent health concerns before they escalate into major issues. Hepatomegaly, characterized by an enlarged liver, poses significant challenges in early detection through CT and MRI scans. The current manual assessment methods are prone to subjectivity and may result in delayed diagnoses, impacting patient care and treatment outcomes

Objective/Aims:

1. **Develop a Deep Learning Model:** Create a robust deep learning model capable of accurately detecting hepatomegaly from CT and MRI scans.
2. **Differentiation of Normal vs. Enlarged Livers:** Train the model to differentiate between scans showing normal liver sizes and those indicative of hepatomegaly.
3. **Enhance Diagnostic Accuracy:** Achieve high sensitivity and specificity in the model's predictions to reduce false positives and false negatives
4. **Dataset Preparation:** Curate a comprehensive dataset of annotated CT and MRI scans representing both normal and hepatomegaly-affected livers to facilitate model training.
5. **Optimize Model Performance:** Fine-tune model architecture and hyperparameters to enhance its ability to generalize across diverse patient populations and imaging variations.
6. **Ethical Considerations:** Ensure transparency in the model's decision-making process, address biases, and maintain patient privacy and confidentiality throughout the project.

II. RELATED WORKS

The Literature Survey delves into the realm of organ segmentation and liver tumor within medical imaging. It provides an extensive exploration of existing methodologies, advancements, challenges, and future directions in these domains. This contributes to the broader field of medical imaging, enhancing diagnostic accuracy, treatment planning, and patient outcomes.

"Segmentation of Liver using Abdominal CT Scan to Detection Liver Disease Area" [2] paper introduces an innovative method for automatically detecting liver disease using Abdominal CT Scan images. Leveraging the Watershed Transform Algorithm the segmentation process accurately locates and isolates the liver from the background. Subsequent application of a binary threshold method further refines the segmentation to pinpoint the affected liver area. The study demonstrates impressive accuracy rates of 81.15% for wide liver segmentation and 98.28% for disease segmentation, establishing the watershed method as a reliable tool for enhancing diagnostic capabilities in liver disease detection using Abdominal CT Scan images.

The research [7] on "A Multiple Layer U-Net, U-Net, for Liver and Liver Tumor Segmentation in CT" study introduces the U n-Net architecture, a variant of the U-Net model, for liver and liver tumor segmentation in CT scans. By incorporating output features from convolution units as skip connections, U n-Net enhances feature utilization within the network nodes. Two variants, U2-Net and U3-Net, are explored, integrating dilated convolution (DC) and a dense structure in network nodes. Evaluation on LiTS and 3DIRCADb datasets demonstrates compelling performance, with U n-Net achieving a Dice's Similarity Coefficient (DSC) of 96.38% for liver segmentation and 73.69% for tumor segmentation on LiTS, and 96.45% for liver and 73.34% for tumor segmentation on 3DIRCADb Comparative analysis showcases superior results compared to recent networks, underscoring the practical utility of U n-Net models in advancing medical image segmentation accuracy and efficiency, crucial for diagnosis and pre-surgery planning.

The research [6] on "Deep Learning-Based Classification of Liver Cancer Histopathology Images Using Only Global Labels" research introduces an automated framework for accurate liver cancer diagnosis using histopathological images. The methodology combines deep learning, transfer learning, and image segmentation techniques to address challenges such as image complexity and limited annotated data. By segmenting images into patches and employing pre-trained Convolutional Neural Networks (CNNs), the framework extracts feature efficiently. Integration of Multiple Instance Learning (MIL) enables image classification based on patch-level features, reducing reliance on specific annotations. The approach demonstrates efficiency in handling large-scale images and mitigates data scarcity through transfer learning. Detailed sections cover methodology, dataset description, experimental setup, classification metrics, and findings, with potential to revolutionize liver cancer diagnosis through scalable and accurate histopathological image analysis.

The study [3] on "Implementation of Liver Segmentation from Computed Tomography (CT) Images Using Deep Learning" addresses the labor-intensive and error-prone manual approach faced by medical professionals. To overcome this, a methodology employing deep learning techniques is proposed, leveraging the UNet architecture, MONAI, and PyTorch for automated segmentation. Deep learning offers robustness and efficiency, with UNet capturing global and local features effectively. MONAI enhances efficiency with pre-built tools for medical image analysis. The model is trained on a CT scan dataset, adjusting parameters through backpropagation for accurate segmentation. Evaluation metrics demonstrate the model's accuracy, sensitivity, specificity, and dice cofficient, aiming to match manual segmentation while considering efficiency. Limitations include data quality reliance and interpretability challenges, with future scope including multi-organ segmentation, fine-tuning, real-time optimization, clinical integration, and ethical considerations.

The invention presented [1] in "Hepatomegaly Diagnosis by Measuring the Liver Dimensions and Volume using Computed Tomography" tackles the challenges associated with accurately measuring liver size, crucial for hepatomegaly diagnosis. Existing methodologies lack standardized classification systems for varying liver shapes, leading to inaccuracies. Researchers conducted a retrospective analysis of 603 abdominal CT scans, employing advanced visual analysis and 3D reconstruction for liver volume calculation. Their methodology utilizing IntelliSpace Portal 9.0 software, yielded promising results, enhancing diagnostic accuracy by considering nuanced liver shapes. Meticulous CT image analysis and derivation of specific formulas for different liver types (I-IV) were conducted, yielding AUC values ranging from 0.87 to 0.93 and specificity values ranging from 84% to 91%. Despite limitations, such as sample size and imaging protocol variations, the study encourages standardized liver form classification and the integration of proposed formulas into clinical practice. This research significantly advances liver size measurement understanding, offering an improved approach to hepatomegaly diagnosis with implications for enhanced patient care.

The Study [5] on "Deep Learning CT-based Quantitative Visualization Tool for Liver Volume Estimation: Defining Normal and Hepatomegaly" Conventional linear methods for hepatomegaly assessment often fail to represent the liver's 3D morphology accurately. A retrospective analysis of 3065 patients undergoing CT scans introduced a sophisticated deep learning algorithm for liver segmentation. Patient weight emerged as a critical determinant, establishing a weight-based upper limit of normal hepatomegaly. The fully automated CT- based artificial intelligence tool provided a more accurate assessment compared to traditional linear measures. Patient weight introduced a weight-based threshold for hepatomegaly, highlighting the limitations of linear measurements. Acknowledging limitations, such as potential selection bias, the study suggests future research directions like prospective studies and algorithm refinement, paving the way for advancements in hepatomegaly diagnosis.

The research paper [8] on "Automated CT and MRI Liver Segmentation and Biometry Using a Generalized Convolutional Neural Network" introduces a versatile convolutional neural network (CNN) for automated liver segmentation, showcasing its adaptability across diverse imaging modalities such as contrast-enhanced and unenhanced CT, and hepatobiliary phase T1-weighted MRI. The CNN's transfer learning capability enables effective generalization with minimal additional training data, outperforming traditional single-modality methods. Investigation into training data size demonstrates substantial segmentation accuracy improvements, with notable enhancements in Dice score plateauing around 10 CT image sets and 20 contrast-enhanced MRI datasets. Augmentation of training data enhances CNN's robustness and performance in liver volumetry and proton density fat fraction estimation, offering efficient hepatomegaly assessments and objective hepatic tissue characterization. While promising for clinical workflows, careful validation and outlier consideration are essential before widespread clinical integration.

The research paper [4] "Assessing Hepatomegaly: Automated Volumetric Analysis of the Liver" aimed to enhance hepatomegaly detection by introducing volumetric nomograms and assessing radiologists' performance. Automated liver segmentation demonstrated high accuracy, with a 96.2% volume overlap and 2.2% volume error compared to manual measurements. Nomograms (H scores), normalized to body surface area, were established, offering a quantitative tool for hepatomegaly identification. The results indicated robustness in automated liver segmentation, paving the way for improved clinical assessments. The H scores, defining mild and massive hepatomegaly cutoffs, exhibited high concordance with clinical interpretations. Radiologists demonstrated sensitivity rates of 84.4% for all hepatomegaly cases and 100.0% for massive hepatomegaly, emphasizing the potential of automated volumetric assessments to enhance diagnostic accuracy. In discussion, the study underscored the reliability of the automated segmentation method, aligning well with manual assessments. The introduced H scores provided a quantitative and normalized approach to hepatomegaly detection, outperforming traditional methods such as height measurements or visual inspection. Overall, the findings suggest that incorporating automated volumetric assessments could significantly improve hepatomegaly detection in routine clinical practice.

III. SYSTEM DESIGN

The software application design is a progression or improvement of the application, or a system that follows the Software Development Life Cycle (SDLC). The next step after analysis of the entire requirement is design. The main purpose of system design is to attain the entire design of the system, also to catch the idea about the different modules present in the system, relation between the different modules, to know about the purpose of each module, and how all the modules merge to form a complete system. The design gives the overview of the system flow, the architecture and to moreover, provides the common solution for the application.

A. Architectural Diagram

In software or systems engineering, a diagram serves as a visual representation depicting the structure, components, and interactions of a system or application, aiding stakeholders in understanding its design and functionality. The System architecture is shown in Fig.1.In the architecture, a CT image undergoes following process.

1) Image Upload and Preprocessing: The system shall allow users to upload CT and MRI images in DICOM, JPEG, or PNG formats. It shall perform preprocessing tasks such as noise reduction, normalization, and resizing to ensure compatibility with the segmentation model.
2) Segmentation Functionality: The system shall employ a deep CNN model, specifically based on the U-Net architecture, to perform organ segmentation in uploaded images. It shall provide options for automatic segmentation of liver organs upon user request. Users shall have the ability to initiate manual adjustments to the segmentation results for refinement.
3) Comparison and Analysis: The system shall overlay segmented liver organs on original images for visual comparison. The system shall overlay segmented liver organs on original images for visual comparison. Users shall have tools to annotate and mark areas of interest or abnormalities identified during the comparison process. The ReSUNet architecture plays a central role in feature extraction, enhancement, and liver segmentation, integrating images, rotating, reflecting, and making subtle changes to enhance information. The final step involves comparing and classifying the segmented liver area using algorithms like the growing region algorithm to accurately delineate the liver border, facilitating comprehensive analysis for medical professionals to identify abnormalities and make informed decisions

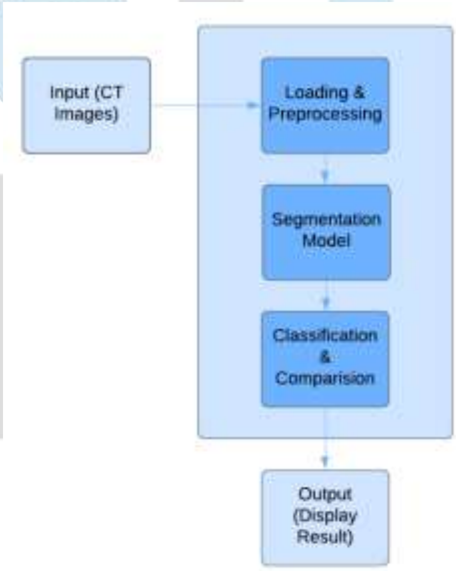

Fig: 1. Architectural Diagram

IV. PREPARE YOUR PAPER BEFORE STYLING

Implementation basically involves putting the design technique into an operational state. This is seen to be the most crucial stage of the project because it connects the system to the user's working procedure. The developer incorporates every design element into the actual workings of the system that will be used. The process of implementation entails setting the created system into use in diverse working environments. The major tasks of the implementation stage is careful planning, examining the system and various primary constraints, designing the methodology in such a way that the changeover phase and also deals with evaluation.

A. Software Tools Used

Front-End Implementation

We have utilized Streamlit for the front end of our project. Streamlit is a Python library designed for rapid development of interactive web applications, particularly for machine learning and data science projects. Unlike traditional web development frameworks, Streamlit allows developers to create web applications directly from Python scripts, eliminating the need for expertise in web technologies such as HTML, CSS,or JavaScript. With its intuitive and user-friendly interface, Streamlit accelerates the development process by providing built-in widgets and functionalities for data visualization, user interaction, and model deployment. In this project, Streamlit was instrumental in designing the user interface and implementing various features using Python.

Back-End Implementation

We chose Python as our backend programming language because our project involves machine learning. The greatest programming language for AI and machine learning is Python. Unlike regular software initiatives, AI projects are unique. The distinctions are in the technology stack, the Expertise needed for an AI-based project, and the requirement for indepth analysis. You should select a programming language that is reliable, adaptable, and equipped with tools to carryout your AI aspirations. All of these features are provided by Python, which is why Python AI applications dominate nowadays. Python aids developers in productivity and self-assurance regarding the software they are creating, from the development through deployment and maintenance. Python offers a number of advantages that make it the best choice for projects involving machine learning and artificial intelligence, including simplicity, consistency, access to excellent libraries and frameworks for these fields, flexibility, platform independence, and a large user base Python Machine Learning Libraries In this paper various Python libraries are used to handle data processing, visualization, and machine learning tasks. These include numpy and pandas for data manipulation, matplotlib. pyplot for plotting, globe for file manipulation, nibabel for handling neuroimaging data, cv2 for computer vision tasks, PIL for image processing, and fatsia for deep learning tasks. Additionally, we employed TensorFlow and Keras for building and training neural networks, and sklearn for machine learning utilities such as train-test splitting.

Tools

Visual Studio Code is a quick yet effective source code editor that runs on Windows, macOS, and Linux. It has builtin support for JavaScript, TypeScript, and Node.js and a robust ecosystem of extensions for other programming languages and runtimes, including C++, C, Java, Python, PHP. The editor, packages, and well-designed debugger of Visual Studio Code help to make programming easier. Its richer plugins also contribute to this. Python text processing packages in Visual Studio Code, which support text augmentation and classification, are used in the project's development.

B. Algorithms Implemented

U-net Architecture

U-Net architecture is a convolutional neural network (CNN) architecture that is widely used especially in the field of biomedical image segmentation. The U-Net architecture is named for its U-shaped structure that includes the encoder and decoder paths. ResUNet, short for Residual U-Net, is a deep learning framework designed for specific tasks in healthcare, particularly extracting specific patterns, such as hearts,liver,from difficult medical images. ReSUNet combines the advantages of two successful companies, ResNet and U-Net, and excels at capturing properties of variables while reducing the complexity of training deep neural networks. ResUNet, short for Residual U-Net, is a deep learning network designed for specific tasks in the medical field, specifically to extract unique patterns from complex medical images such as heart, heart, and heart. ReSUNet combines the advantages of two successful companies, ResNet and U-Net, and is good at capturing the characteristics of different products while reducing the complexity of abstract neural networks. In medical images obtained by tomography (CT) scan. ReSUNet is a combination of ResNet and U-Net architectures, carefully designed to work well in complex applications, primarily in healthcare. ResNet's innovation allows training deep neural networks with residual space without the problem of gradient disappearance. Additionally, it uses an encoder-decoder built on U-Net architecture, which can provide content extraction and clear visualization of the liver in CT images. By integrating these technologies, ReSUNet not only improves the accuracy and efficiency of liver segmentation, but also provides doctors with heartbreaking diagnostic tools and treatment plans. It has the following features: Effective segmentation of medical images. Combined with ResNet and U-Net architectures, ReSUNet uses its strengths to solve different problems in the field. ReSUNet solves the problem of loss by combining ResNet networks, supporting effective training of deep neural networks even when using complex clinical data. It also uses the U-Net encoder-decoder design to provide detailed and precise localization of the liver in CT images. Through this integration, ReSUNet increases the accuracy and efficiency of liver segmentation, providing doctors with reliable tools for liver diagnosis and treatment

V. RESULTS AND DISCUSSION

Upon conducting testing on the model, which involved uploading CT images of the liver and predicting hepatomegaly, the results demonstrated a highly successful outcome. The prediction algorithm accurately identified the presence or absence of hepatomegaly based on the uploaded CT images with a notable degree of precision. This signifies the system's robustness and effectiveness in hepatomegaly detection, showcasing its potential for clinical application. Such reliable performance instills confidence in the algorithm's utility as a diagnostic tool, thereby contributing to improved healthcare outcomes. The paper looks at how to make computer models better at cutting out specific parts of images accurately. Dice coefficient to measure the performance of the model. In the paper the importance of this method ,The data used for training(70%), validation (30%) and testing (10%) are explained. the accuracy graph shown in Fig 2 and Loss detection graph shown in Fig 3 for the ReSUNet model depict its performance during training and validation

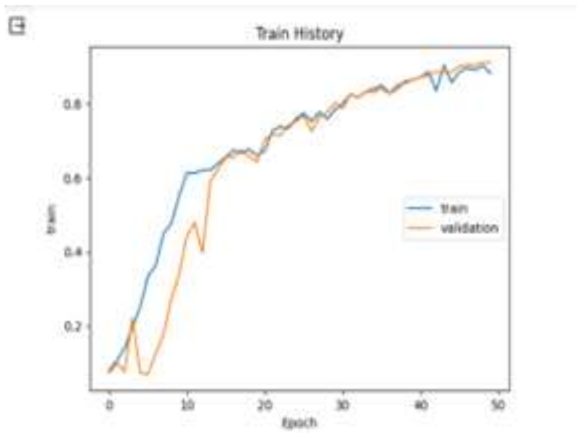

Fig. 2. Graph for Accuracy of the Model

C.

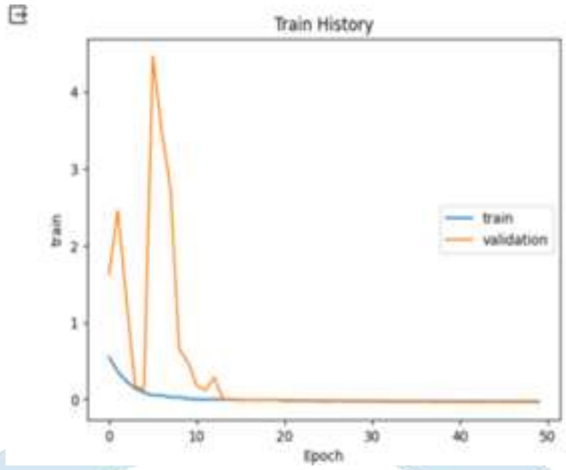

Fig. 3. Graph for Detection of Loss in The Model

D.

In TABLE 1 the training accuracy of the model with respect to the number of epoch's is shown. As depicted, the accuracy of the model, measured by the Dice coefficient, steadily increased with each epoch. Notably, by the tenth epoch, this model achieved an accuracy of 85.95% thereby indicating significant improvement and suggests that the model is learning effectively from the training data.

TABLE I
EPOCHS VS ACCURACY

Number of Epochs	Accuracy of the model
10	57.09%
20	65.96%
30	77.49%
40	86.06%
50	88.02%

TABLE II
TESTING RESULT

Segmentation model	Accuracy for the test data
	85.95%

VI. CONCULSION

The project on the detection of hepatomegaly in the liver through CT image analysis represents a significant advancement in medical diagnostics. By leveraging user provided CT images, our system undergoes preprocessing to isolate and segment the liver region, subsequently calculating its area. Through comparative analysis with healthy liver area benchmarks, our model accurately predicts the presence of hepatomegaly. This streamlined approach offers a non-invasive and efficient method for diagnosing liver enlargement, providing valuable insights for medical professionals and facilitating timely interventions. Moving forward, continued refinement and validation of our model will further enhance its clinical utility, ultimately contributing to improved patient care and outcomes in hepatomegaly management there are several avenues for further exploration and improvement. Continuously refining the model architecture and training process to improve accuracy and efficiency, ensuring reliable hepatomegaly detection in diverse clinical scenarios. Exploring the adaptation of the system for detecting other liver abnormalities or extending its use to different medical imaging modalities, broadening its utility in clinical practice. Another important future aspect of our project involves the creation of algorithms that find the exact location of swellings or bulges in the liver and provide doctors with precise spatial information. This development will allow doctors to make detailed assessments and make surgical plans, making it easier to deal with progress and efficiency.

VII. ACKNOWLDEGMENT

VIII. We thank those responsible for shaping the paper. Without their guidance and help, the experience while constructing the dissertation would not have been so smooth and efficient.

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