**LIVER DISEASE PREDICTION USING MACHINE LEARNING CLASSIFICATION TECHNIQUES**

**ABSTRACT**

Exact automatic liver and tumor segmentation will affect powerfully liver therapy planning procedures, and follow-up reporting, thanks to automation, standardization, and incorporation of full volumetric information. In this work, we propose a fully automatic method for liver tumor segmentation in CT images based on a 2D convolutional deep neural network. We ran our experiments on the (3D-IRCADb 01) datasets and evaluated detection and segmentation performance. Our proposed method achieves segmentation quality for detected tumors comparable to a human expert and is able to detect potentially measurable tumor lesions. To help doctors better diagnose and present personalized curing. in medical practice, it is often required to make segmentation and visualization for live tumor parts. Because of the huge number of slices in the input image, developing an automatic and efficient segmentation technique is very preferred by physicians. Although due to the noise in the scan and the similar pixel weight of liver tumors with surrounding cells, besides both size, position, and shape of tumors also is different for each patient, automatic liver tumor segmentation is still a difficult task. Liver and tumor segmentation is a bottleneck for any system. In this problem, deep learning and image processing techniques are adopted for semantic classification to fit liver CT scan segmentation.

**EXISTING SYSTEM**

Existing systems for liver disease prediction and diagnosis encompass a spectrum of methodologies and technologies. Traditional approaches often involve manual segmentation performed by radiologists, which is labor-intensive, time-consuming, and susceptible to inter-observer variability. While semi-automatic segmentation tools aim to alleviate some of these challenges by assisting radiologists in the segmentation process, they still require human intervention for refinement, limiting their efficiency. Automated segmentation techniques, including those employing machine learning algorithms such as random forests, support vector machines, and deep learning-based approaches, offer potential solutions. However, these methods may suffer from issues such as overfitting, limited generalizability to diverse datasets, and difficulties in handling complex anatomical variations and imaging artifacts. Deep learning-based approaches, particularly convolutional neural networks (CNNs) like U-Net, have shown promise in accurately segmenting liver tumors in CT images. Nevertheless, they often require large annotated datasets for training, extensive computational resources, and careful parameter tuning. Additionally, the integration of segmentation and classification models into unified systems presents its own set of challenges, including model integration complexities, increased computational overhead, and potential performance trade-offs. Furthermore, while commercial software solutions offer automated tools for liver tumor segmentation and disease prediction, they may be expensive, proprietary, and lack transparency in their algorithms. Overall, while existing systems have made significant strides in automating liver disease prediction, addressing these drawbacks remains crucial for their widespread adoption and clinical utility.

**DRAWBACKS**

* Labor-intensive, time-consuming, and prone to errors.
* Still require human intervention, limiting automation.
* May suffer from overfitting, limited generalizability, and difficulty in handling complex variations.
* Require large datasets, extensive computational resources, and careful parameter tuning.

**PROPOSED SYSTEM**

The proposed system is designed to automate liver disease prediction using machine learning classification techniques, integrating segmentation and classification models to analyze CT images. The system begins with a data preprocessing module to enhance image quality and standardize intensities. Subsequently, the liver tumor segmentation module, based on the U-Net architecture, automatically delineates liver and tumor regions within the CT scans. Following segmentation, a feature extraction module is employed to capture relevant characteristics from the segmented regions, encompassing shape descriptors, texture features, and intensity statistics. These features serve as input to the classification model module, a convolutional neural network (CNN), tailored for liver disease classification. Trained to differentiate between various liver conditions, including benign and malignant tumors or cirrhosis, the CNN leverages the extracted features to make accurate predictions. The integration module harmonizes the segmentation and classification outputs, providing a unified prediction system. Throughout the development process, the training and optimization module refines model parameters to enhance segmentation accuracy and classification performance. The system's effectiveness is evaluated through metrics such as accuracy, sensitivity, specificity, and the Dice similarity coefficient, ensuring robustness and generalizability. Ultimately, this automated approach aims to streamline diagnosis and treatment planning for liver diseases, empowering clinicians with efficient and accurate decision-making tools.

**ADVANTAGES**

* Automates the process of liver tumor segmentation and disease prediction, reducing the reliance on manual interpretation.
* Integrates segmentation and classification techniques for comprehensive liver disease assessment.
* Leverages state-of-the-art deep learning architectures (U-Net and CNN) for accurate segmentation and classification.
* Provides a scalable and efficient solution for liver disease prediction in clinical settings.

**Hardware Requirements**

The most common set of requirements defined by any operating system or software application is the physical computer resources, also known as hardware. A hardware requirements list is often accompanied by a hardware compatibility list (HCL), especially in case of operating systems. An HCL lists tested, compatibility and sometimes incompatible hardware devices for a particular operating system or application. The following sub-sections discuss the various aspects of hardware requirements.

* System : Intel core I3 processer 64 bit.
* Monitor : LED.
* Mouse : Logitech.
* Ram : 4.00 GB.

**Software Requirements:**

Software Requirements deal with defining software resource requirements and pre-requisites that need to be installed on a computer to provide optimal functioning of an application. These requirements or pre-requisites are generally not included in the software installation package and need to be installed separately before the software is installed.

* Operating system : Windows 64 bit
* Language : Python
* Platform : Anaconda3

**BLOCK DIAGRAM**

**Preprocessing**

**Input CT scan images**

**Noise Removal**

**Wiener Filter**

**Tumor or No Tumor**

**Image Segmentation (U-NET)**

**Training Dataset**

**CNN Classification**

**Testing an Image**

**FLOW DIAGRAM**

START

DATASET COLLECTION

PREPROCESSING

SEGMENTATION (U-NET)

TRAINING, TEST & VALIDATION

ABNORMAL

NORMAL

MODEL GENERATED (CNN)

UPLOAD INPUT

PREDICTED

PREDICT TUMOR OR NO TUMOR

**MODULE DESCRIPTION**

The proposed system aims to develop an integrated solution for liver disease prediction using machine learning classification techniques, focusing on automated liver tumor segmentation and disease classification in CT images.

**Preprocessing**

The CT images are preprocessed to enhance image quality, reduce noise, and normalize intensities. Techniques such as denoising filters, contrast enhancement, and histogram equalization may be employed.

**Liver Tumor Segmentation (U-Net)**

* Utilize the U-Net architecture for automated liver tumor segmentation in CT images.
* Train the U-Net model using annotated CT scans to accurately delineate liver and tumor regions.

**Feature Extraction**

* Extract relevant features from segmented liver and tumor regions, such as shape descriptors, texture features, and intensity statistics.
* These features serve as input to the classification model for liver disease prediction.

**Classification Model (CNN)**

* Design and implement a convolutional neural network (CNN) architecture for liver disease classification.
* Train the CNN model using extracted features from CT images to predict the presence or absence of liver disease.
* Fine-tune the CNN model parameters to optimize classification performance.

**Integration and Prediction**

* Integrate the U-Net segmentation model and CNN classification model into a unified system for liver disease prediction.
* Combine segmented liver and tumor regions with classification features for comprehensive disease prediction.
* Generate predictions for liver disease presence and severity based on the integrated model’s output.