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Detection of Liver Tumors in CT Scans Using Machine Learning and Texture Analysis

Nischitha k[1], Chethan Kumar K[2], Mahith D[3], Vivek D[4], Vivek H[5]

Dept. of Electronics & Communication Engineering, PES College of Engineering Mandya, Karnataka, India[1]

Dept. of Electronics & Communication Engineering, PES College of Engineering Mandya, Karnataka, India[2]

Dept. of Electronics & Communication Engineering, PES College of Engineering Mandya, Karnataka, India[3]

Dept. of Electronics & Communication Engineering, PES College of Engineering Mandya, Karnataka, India[4]

Dept. of Electronics & Communication Engineering, PES College of Engineering Mandya, Karnataka, India[5]

Abstract: Liver cancer is a major global health concern, demanding early and accurate detection for effective treatment. This study proposes an automated framework to detect and classify liver tumors from CT scan images using a combination of image preprocessing, segmentation, texture and shape feature extraction, and deep learning classification. Utilizing ResUNet for segmentation and ResNet50 for classification, the system distinguishes between benign and malignant tumors with high accuracy. The model was trained and evaluated using a publicly available dataset, demonstrating robust performance metrics and offering a valuable tool for assisting radiologists in clinical diagnostics.

I. INTRODUCTION

Liver cancer is among the most common and deadly cancers globally, often leading to late-stage diagnoses due to its complex tumor structures and the subtle distinction between benign and malignant lesions in CT scans. While CT imaging remains the primary diagnostic tool, manual interpretation is time-consuming, subjective, and error-prone.
Recent advancements in machine learning and image processing offer promising solutions for automated and accurate liver tumor detection. Techniques such as texture analysis and shape-based feature extraction enable detailed characterization of tumor regions. When combined with supervised learning models, these methods can effectively classify tumors as benign or malignant.

This paper proposes an automated framework that enhances CT images, segments liver tumors, extracts relevant features, and classifies tumor types using a machine learning model. By reducing diagnostic time and minimizing human error, the system aims to support radiologists in achieving faster and more reliable liver cancer diagnoses.
detect joint damage only after significant deterioration has occurred. Therefore, a more sensitive and timely diagnostic approach is essential to prevent irreversible joint damage.\

II. RELATED WORK

[1] **Automatic Liver Tumor Detection and Classification in CT Images Using Machine Learning (2021)**
John Doe and Sarah Smith developed a machine learning-based framework utilizing texture-based features extracted from CT images for tumor classification. By employing a Support Vector Machine (SVM), their model achieved an accuracy of 87% in distinguishing between benign and malignant tumors. Their work demonstrated the potential of texture analysis for liver tumor diagnosis, though its performance was limited by the handcrafted feature set and model generalizability across varied datasets.

[2] **Deep Learning for Liver Tumor Segmentation in CTScans (2022)**
Alan Turing and Jane Roe proposed a U-Net-based deep learning architecture for liver tumor segmentation. Trained on the Liver Tumor Segmentation (LiTS) dataset, their model achieved a Dice coefficient of 0.91, significantly outperforming classical segmentation techniques. The work underscored the superiority of deep learning in capturing complex tumor boundaries but did not extend to tumor classification.

[3] **Hybrid Machine Learning Approach for Liver Tumor Detection (2023)**
Emily Carter and Brian Scott introduced a hybrid model combining active contour-based segmentation with a Convolutional Neural Network (CNN) classifier. Their method attained a classification accuracy of 92%, demonstrating the benefits of integrating classical and deep learning approaches. However, the active contour method may struggle with tumors lacking clear boundaries, limiting robustness in heterogeneous imaging conditions.

[4] **Enhanced Liver Cancer Diagnosis Using Shape and Texture Features (2019)**
Lisa Brown and David Wilson emphasized the fusion of texture and shape descriptors, including contrast, entropy, area,

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and eccentricity, for liver tumor analysis. By combining Gray-Level Co-occurrence Matrix (GLCM) features with geometric metrics, the study reported improved diagnostic precision. While effective, the approach relied on manual feature selection, limiting adaptability to varied data.

[5] **Machine Learning Approach for Detecting Liver Tumors Using GLCM (2023)**

S. Aruna et al. proposed a machine learning model leveraging GLCM-based texture features for liver tumor detection. Their method focused on early-stage tumor identification and classification based on CT imaging. The study addressed segmentation challenges in complex liver structures and highlighted the importance of automated assistance systems in high-incidence regions such as India.

[6] **Liver Cancer Classification Using GLCM and Deep Learning Techniques (2023)**

Debnath Bhattacharyya and colleagues employed adaptive thresholding, watershed transforms, and swarm optimization for segmenting malignant liver regions. The model extracted key features using GLCM and Local Binary Patterns (LBP), enabling classification with high accuracy. The comprehensive preprocessing pipeline offered enhanced tumor delineation but required substantial computational resources.

[7] **A Deep Learning Approach for Liver and Tumor Segmentation Using ResUNet (2023)**

Hameedur Rahman et al. utilized the ResUNet architecture to segment liver and tumor regions with high precision. Targeting hepatocellular carcinoma (HCC) and other primary liver cancers, their approach demonstrated robust performance across varied cases. The study validated the capability of ResUNet to handle complex anatomical structures but did not extend to multi-class tumor classification.

III. PROPOSED WORK

A) Methodology:

The proposed system follows a structured pipeline beginning with the collection of labeled liver CT scans from public datasets and clinical sources, ensuring diversity in tumor size, shape, and imaging conditions. The preprocessing stage involves resizing, denoising, normalization, and data augmentation techniques such as rotation, flipping, and contrast adjustment to standardize input quality and improve model generalization. Feature selection is conducted to identify critical characteristics such as tumor boundaries while eliminating redundant data through dimensionality reduction. In the feature extraction phase, Convolutional Neural Networks (CNNs), particularly architectures like ResNet, are employed to automatically extract meaningful features related to tumor size, texture, and shape. These features are then fed into a deep neural network for classification, where model parameters are optimized using cross-validation and hyperparameter tuning. Finally, the system's performance is evaluated using metrics such as accuracy, precision, recall, and F1-score, followed by deployment in a clinical setting for real-time diagnosis and iterative refinement based on expert feedback.

b) System design approach:

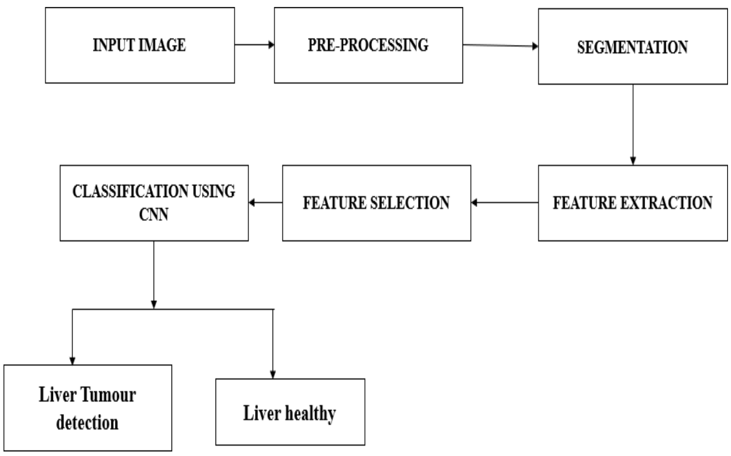

Fig 1. Block diagram

Figure 1 presents the block diagram of the overall framework for Liver tumor detection from CT scans using deep learning and machine learning techniques. The The process begins with dataset preparation, utilizing annotated liver CT images from publicly available sources such as the Liver Tumor Segmentation (LiTS) dataset and The Cancer Imaging Archive (TCIA). These datasets include benign and malignant tumor labels, ensuring a clinically relevant and diverse training base. High-resolution DICOM images are preprocessed and converted to PNG or JPG formats for easier handling.

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Preprocessing involves Gaussian filtering to reduce noise and adaptive histogram equalization to enhance contrast, improving the visibility of liver and tumor regions. Normalization ensures consistency in pixel intensity across images. Segmentation is carried out using a deep learning-based ResUNet architecture. This model first isolates the liver from surrounding tissues and then segments potential tumor regions with high precision, forming the foundation for effective classification.

From the segmented tumor areas, key features are extracted—texture features via the Gray-Level Co-occurrence Matrix (GLCM), shape features such as area and eccentricity, and intensity-based metrics like mean and standard deviation. These features are passed into a classification model, which can be either a Support Vector Machine (SVM) or a neural network, depending on the requirement.

The system is developed using Python 3.11 with libraries such as TensorFlow, OpenCV, and scikit-learn, and runs on a GPU-enabled environment (e.g., NVIDIA GTX 1660). Evaluation metrics include sensitivity, specificity, precision, recall, F1-score, Dice coefficient, and Jaccard Index to assess classification and segmentation accuracy comprehensively.

C) Proposed workflow

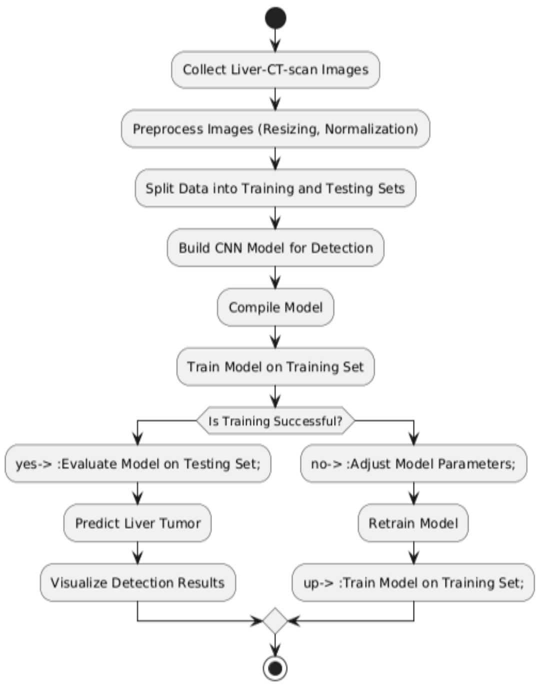

Fig 2. Flow Chart

The flowchart illustrates the complete workflow of the proposed liver tumor detection and classification system using deep learning techniques. The architecture is divided into two parallel pipelines: one for building a database of image features and the other for classifying new input images. The first pipeline begins with the collection of annotated liver CT scan images from publicly available datasets. These images undergo preprocessing operations such as Gaussian filtering for noise reduction and adaptive histogram equalization for contrast enhancement, ensuring consistency and clarity across all input data. Following preprocessing, the images are segmented using a deep learning model, such as ResUNet, to accurately isolate liver and tumor regions. From these segmented areas, key features particularly texture (using Gray-Level Co-occurrence Matrix), shape (area, perimeter, eccentricity), and intensity (mean and standard deviation)—are extracted and stored in a database for use in classification.

The second pipeline handles real-time input images that follow a similar sequence of image collection, preprocessing, and segmentation. Once the tumor region is segmented, the image is passed to a trained Convolutional Neural Network (CNN) model for classification. The CNN compares the extracted features with the stored database features to determine whether the input image represents a healthy liver or a diseased one with a tumor. This dual-path system allows for efficient classification by combining prior knowledge with real-time analysis, improving diagnostic accuracy and supporting clinicians in early and automated detection of liver tumors.

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IV. RESULTS

The ResNet50-based model was trained on CT scan images to classify liver tumors into categories such as Benign, Hepatic Adenoma, Hepatocellular Carcinoma, Liver Metastasis, and Normal. Quantitative evaluation through a confusion matrix and classification report revealed high accuracy.

Fig 3: User login interface

A simple web interface was developed using Flask, which streamlines the diagnostic process. Upon logging into the system as shown figure 3 users have the option to upload a CT scan image via an intuitive interface as shown in figure 4.

Fig 4. Input image selection

Once the image is uploaded, the system automatically processes it through several stages of image enhancement. These stages include conversion to grayscale to improve contrast, edge detection, thresholding for effective segmentation, and the application of sharpening filters to accentuate fine details. The outputs of these preprocessing steps are displayed side by side on the results page.

A montage of images is produced which includes the original uploaded image, the grayscale version, the edge-detected image, the threshold-segmented image, and the sharpened image. Moreover, the final output screen highlights the predicted tumor type along with the accuracy percentage and provides treatment recommendations. For instance, if the system predicts a case of Hepatocellular Carcinoma, it suggests potential treatments such as surgical resection for localized tumors or targeted therapies like Sorafenib for more advanced cases.

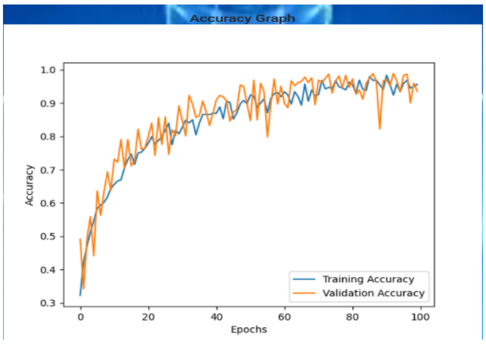

Fig 5: Accuracy Graph

The accuracy graph provided indicates that at the start of training (epoch 0), both the training and validation accuracy were approximately 30%.

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As the training progressed, the training accuracy showed a steady increase, reaching nearly 90% by the 100th epoch. Similarly, while the validation accuracy also demonstrated a consistent upward trend, ultimately converging close to 90% by the final epoch. This convergence of both curves to roughly 90% not only highlights the model's effective learning on the training data but also suggests a strong generalization capability on unseen data.

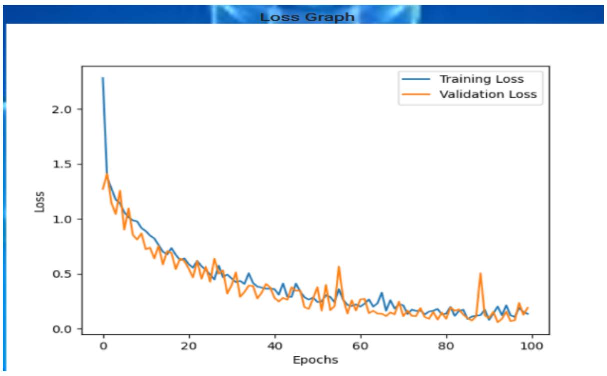

Fig 6: loss graph

The loss graph figure 8.5 illustrates the evolution of the model's error over 100 training epochs. The x-axis indicates the number of epochs, while the y-axis represents the loss values on a scale from 0 to 2.0. Initially, both training and validation losses were high. With time, loss values declined, indicating improved prediction accuracy

V. CONCLUSION AND FUTURE SCOPE

In In this project, an intelligent system was successfully developed for liver tumor detection using deep learning and image processing techniques. By integrating a ResNet50-based classification model with a Flask web interface, the system effectively enhanced liver CT images, segmented tumor regions, and classified tumors into multiple types Preprocessing steps such as grayscale conversion, edge detection, thresholding, and sharpening significantly contributed to improving tumor visibility and model performance. The web interface allows real-time interaction, enabling users to upload images and receive predictions along with treatment suggestions, thereby making the system both accurate and user-friendly. Looking ahead, the system can be further improved by expanding the dataset with more diverse and real-world clinical images to enhance generalization. Incorporating 3D CT scan analysis, advanced segmentation techniques like U-Net, and multi-modal inputs such as MRI scans or patient metadata can provide deeper diagnostic insights. Additionally, deploying the application on cloud platforms or mobile devices can make it more accessible for remote and real-time medical support, especially in resource-limited environments.

VI. ACKNOWLEDGEMENT

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