Comprehensive Liver Tumor Detection and Classification of its Stages Using Deep Learning and Image Processing

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Abstract: This work talks about the deep learning framework for the detection and classification of liver tumors automatically in CT scan using convolutional neural networks (CNNs). The method involves pre-processing steps like contrast improvement, noise reduction, and image scaling to enhance image quality adding resizing, histogram equalization, and application of a bilateral filter for noise removal. For improved localization, image-based segmentation is then carried out. The CNN is used for binary classification, which distinguishes between benign and malignant tumours. If a tumor is determined to be malignant, it is further classified into several phases using a secondary CNN-based categorization method. This multi-phase approach yields valuable insights into the course of liver tumor growth. The methodology combines deep learning classification with state-of-the-art image processing techniques to give an all-inclusive framework for efficient and thorough liver tumor analysis in medical imaging.
Keywords: Computed Tomography (CT), Convolution Neural Network, Deep learning, K – Means Image Based Segmentation and Accuracy, Liver tumors.

I. INTRODUCTION

When cells begin to multiply more quickly, an abnormal lump of tissue known as a tumor forms [5]. Although both forms of liver tumours are possible, benign liver tumours are more common than malignant ones. The most prevailing primary liver cancer is Hepatocellular carcinoma, while the most commonly known benign liver tumor is hepatic hemangioma. The best course of treatment is determined after diagnosing the stage at which Liver tumor is [5]. Options for treatment could include radiation therapy, chemotherapy, liver transplantation, surgery, or targeted therapies.

Deep learning techniques have been applied extensively in medical imaging recently, particularly in the segmentation of liver and liver tumours. For instance, a deep learning strategy has been put out to use UNet++ to segment liver tumours in magnetic resonance imaging (MR). This methodology fits the requirements of extract series analysis and offers a methodological foundation for automated liver tumor segmentation. It also enhances delineation efficiency. Deep learning and radio engineering [1]. Furthermore, to detect liver tumours, a deep learning model based on the Coot Extreme Learning model was created [2]. This model can be used to estimate the usable volume of the liver as well as the size shape add location of the tumor, enabling More precise changes in the treatment plan. In addition, a deep learning automatic lever segmentation from contrast enhanced city (PADLLS) in bracket pipeline combining multiple DCNNs trained to segment the liver from contrast- enhanced CT scans was developed and implemented [3].

The proposed model for automated identification of liver tumors in CT images utilizes our deep learning framework based on convolutional neural networks (CNNs). The process begins with preprocessing steps to enhance image quality adding resizing, histogram equalization, and application of a bilateral filter for noise removal. Further refinement is achieved through K means image-based segmentation, improving localization accuracy frequently, the CNN is utilized for binary classification distinguishing between benign and malignant tumors. In case where the CNN identifies a tumor as malignant, an additional CNN-based classification system is implemented to categorize the malignant tumors into specific stages at early stage, intermediate stage and metastatic stage. This comprehensive approach integrates advanced image processing technique with deep learning classification providing both accurate humor detection and detailed insights into the malignant processing of liver tumor in city images. The sequential application of preprocessing and CNN based classification ensures a robust and nuanced analysis of liver pathology

In addition, ResUNet, which has been shown to be very robust in image variability estimation, has been proposed as a deep learning tool for liver and tumor segmentation in CT images. This makes ResUNet suitable for fully automated liver and tumor segmentation based on CT volumes [4]. By providing oncologists with advice both before and after surgery, these deep learning techniques have transformed medical imaging in a number of areas, including the segmentation of liver and liver tumours. They may also enhance treatment planning, decrease manual labour, and raise the success rate of liver cancer procedures.

II. LITERATURE REVIEW

In the field of medical imaging, especially in the detection and diagnosis of liver cancer deep learning and machine learning techniques are effectively used. In improving the accuracy and efficiency of liver cancer detection, especially in classification of liver tumor based on imaging data these methods have shown promising results [1].

The potential of this technique shows that the method achieved high accuracy of liver tumor detection and segmentation. A U-Net serial network for 3D tumor image reconstruction to detect hepatocellular carcinoma was developed [2].

The proposed network achieved high accuracy in reconstructing 3D tumor images, which can be useful for liver cancer diagnosis and treatment planning. Xiong et al. presented a model which can be adapted for liver tumor segmentation on CT or MRI images [3].

This approach can help reduce the need for large annotated datasets, which can be time-consuming and expensive to acquire. Karthik et al. proposed a method for ischemic lesion delineation in brain MR using an alert fully convolutional network [4].

This approach can be adapted for liver tumor segmentation, especially in cases where tumor boundaries are not clearly defined. Manjunath et al. developed an algorithm for the same [5].

High accuracy was achieved in the proposed model which shows it's potential in liver cancer diagnosis. A report was presented which is not directly related to liver cancer but shows potential of machine learning method. Also, a review was conducted of medical imaging using the same techniques [6,7].

Liver tumor detection from CT images using deep learning techniques. Khoshkhabar et al. (2023) and Rex and Cantlie discuss the challenges of accurately segmenting liver tumors due to overlapping intensity and soft tissue variability. Khoshkhabar et al. (2023) presented a Graph Convolutional Network and hybrid ResUNet model that combines ResNet and UNet architectures to improve liver and tumor segmentation accuracy. In addition, Khoshkhabar et al. (2023) used a CNN algorithm for liver tumor segmentation, which achieved high accuracy and recall rate. These studies highlight the importance of accurate liver tumor segmentation for early diagnosis and follow-up. Overall, the accuracy and efficiency of liver tumor segmentation have been greatly improved by the use of this technique, enabling more accurate and timely diagnosis [17]

In summary, this technique has shown promising results in improving the accuracy and efficiency of liver tumor diagnosis, mainly in the classification and segmentation of liver tumors based on imaging data. However, challenges remain in the development and implementation of these techniques in clinical practice, including the need for large annotated datasets and the need for validation and testing in clinical settings.

III. EXISTING MODEL

Image preprocessing in medical image analysis includes important steps such as noise reduction, enhancement, normalization and standardization to extract features that improve the quality of the raw image.[1] Normalization and segmentation techniques adjust image values, while noise reduction improves resolution and removes unwanted elements for easier post- processing [1,2].

Most widely used machine algorithm for classification and regression which combines multiple classifiers to improve the performance of model is Random Forest. It aggregates predictions from individual trees to make final decisions based on majority voting, enhancing accuracy and robustness [3]. MATLAB provides various functions like contrast enhancement, & color space conversion to tasks such as resizing, rotation, and normalization. These features optimize image quality, preparing images for analytical applications such as computer vision and medical image analysis. Random forest (RF) classifiers, implemented in MATLAB via the "fitrensemble" function, generate multiple decision trees during training by randomly selecting feature subsets and data samples. This randomness and completeness reduce overfitting and improves generalizability. MATLAB's RF algorithm allows users to define different parameters to adapt models to specific data complexity. The Fitrensemble feature facilitates RF model generation by combining decision trees, enabling parallel training and prediction to improve accuracy and generalization RF classifiers excel at high-dimensional data, nonlinear relationships and platform relevance analysis. The MATLAB RF application simplifies the training, validation, and development of RF models in fields such as finance healthcare and imaging [1,3].

In addition, precision measures true positive predictions, recall identifies relevant cases, and F1 scores balance precision and recall. Entropy, a measure of uncertainty, can be calculated in MATLAB using Shannon's entropy formula, which helps estimate the randomness of a system. [3]

Matlab's Random Forest classifiers are robust, accurate and efficient for classification tasks, offering ease of use, feature importance information and high-dimensional data processing capabilities. The Fitrensemble function streamlines the implementation of the RF model, making it the preferred choice for ensemble learning tasks involving decision trees.

The existing model has several drawbacks, including the need for precise parameters turning, lack of interpretability, high computational cost, relevance on RGB to gray conversions, lower accuracy compared to deep learning, limited effectiveness across various data types, and the potential omission of important tumor-related details when focusing mainly on texture through GLCM analysis.

IV. PROPOSED MODEL

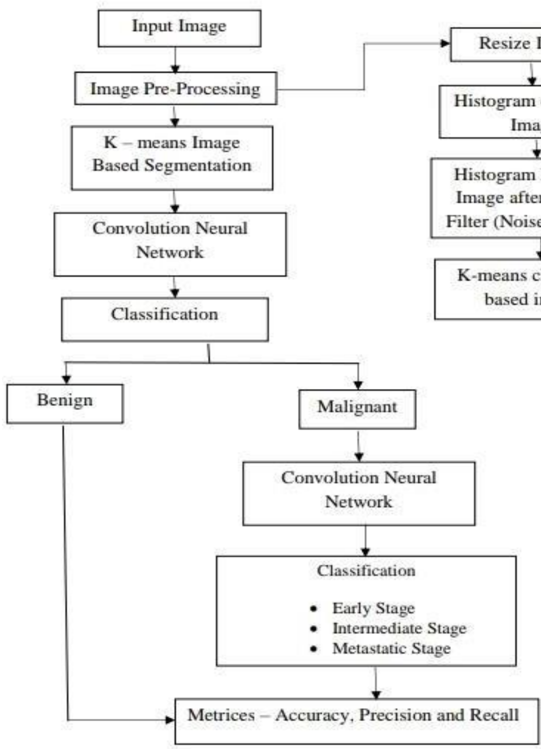

Fig. 1: Block diagram of Proposed model

The proposed model for identifying the liver tumor automatically in CT images utilizes a deep learning model based on CNN. The process begins with resizing in which images are resized to standard size to ensure consistency and reduce computational complexity, to enhance the contract of the image histogram equalization is performed and a bilateral filter is applied for noise removal. After completing this process images are segmented using K-means image-based segmentation to segment the liver tumor from the surrounding tissues based on image intensity. Now CNN is used for binary classification of liver tumor.

CNN are strong deep learning system to analyze data of images, and understand how to calculate the number of parameters in a CNN is critical to designing and training effective models. The number of parameters in a CNN is the sum of the learning elements of each layer, which are usually weight matrices or filters. To calculate the number of parameters for a convolution layer, you multiply the height, width, and depth of the filter by the number of filters in current layer and add one to displacement period of each filter. For example, if the filter size of the convolutional layer is 3*3 & 16 filters the number of parameters would be (3*3*16) +16 = 144. In addition to convolutional layers CNNs also include other types of layers like the layers which are connected and fully connected. Blending layers have no parameters to learn because they simply sample the input features, maps by taking the max. or average in sliding window. The layers which are fully connected, have a large number of parameters because it's each neuron it's connected to its neuron in previous state to calculate the number of parameters for this you need to multiply the number of input neurons by the number of output neurons and add 1 to the displacement period of each output neuron understanding the number of parameters in CNN is important for several reasons. First it can help you design model that is the right size for your data set. A model with an excessive number of patterns may over fit and be enable to generalize fresh data, whereas a model with an insufficient number of patterns may not be able to discover the underlying pattern in the data. Second, the number of parameters affects the computational resources required to train the model. A model with many parameters may require longer training time and more memory. Finally, the number of parameters can affect the interpretability of the model. A model with a small number of parameters can be easier to understand and interpret than a model with many parameters. In summary, calculating the number of CNN parameters is an important step in designing and training effective image analysis models. By understanding the number of parameters in each layer, you can design an appropriately large model for your dataset, optimize computing resources for training, and improve model interpretability. CNN is one of a unique kind of neural network intended for processing data. Grid- organized data, like pictures. Convolutional, pooling, fully linked, and normalizing layers are amongst the layers that make up this structure. Convolutional layers generate features, maps that emphasize the features they have identify input by applying filters. Combining layers to sample the input to reduce computation and parameters. Fully connected layers connect all neurons for final classification or regression tasks. Normalization levels normalize activations and gradients to facilitate training. In MATLAB, "accuracy" is an important metric for evaluating classification models, as it measures the proportion of correctly classified samples. Accuracy focuses on the accuracy of positive predictions, the recall of identifying significant cases, the sensitivity of correctly identifying positive cases, and the specificity of true negative predictions. Based on information theory, entropy quantifies the uncertainty of a system by calculating the randomness or unpredictability of outcomes. The matrix, which provide details on the accuracy, precision, recall, & effective handling of classification and regression tasks by the models, are critical in assessing the efficacy and efficiency of the machine learning models. Understanding and using these metrics is important to optimize model performance and ensure reliable predictions in various machine learning applications.

V. RESULT

Fig. 2: Input Image

Fig. 3: Histogram Equalized Image

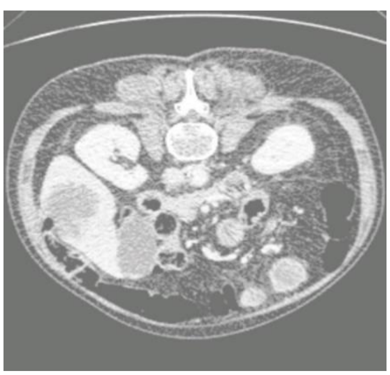

Fig. 4: Histogram equalized image after bilateral filter (Noise Removal)

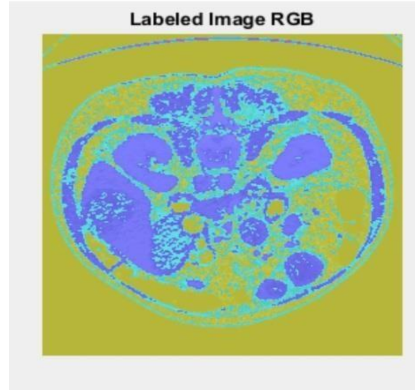

Fig. 5: Labeled RGB Image

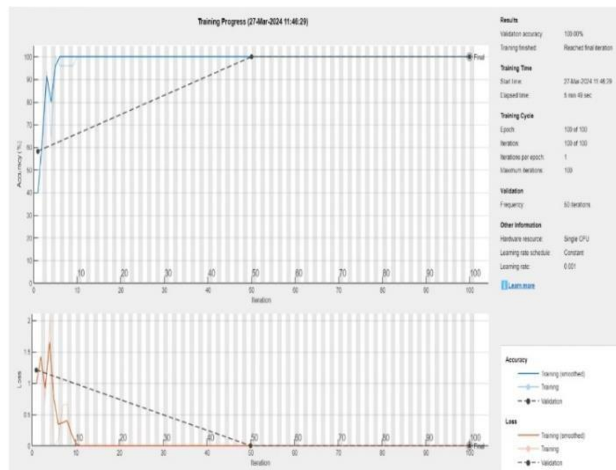

Fig. 6: Training Progress

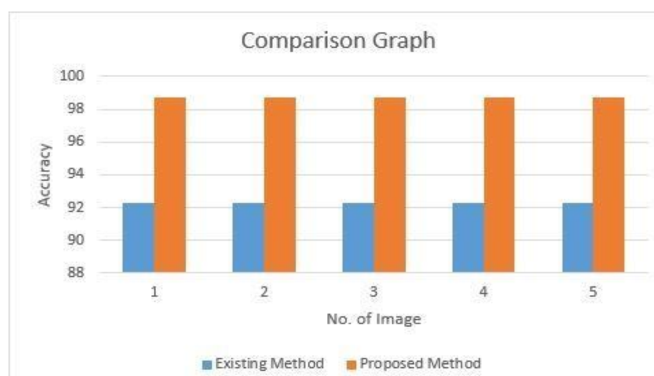

Fig. 7: Overall accuracy comparison graph between proposed and existing method

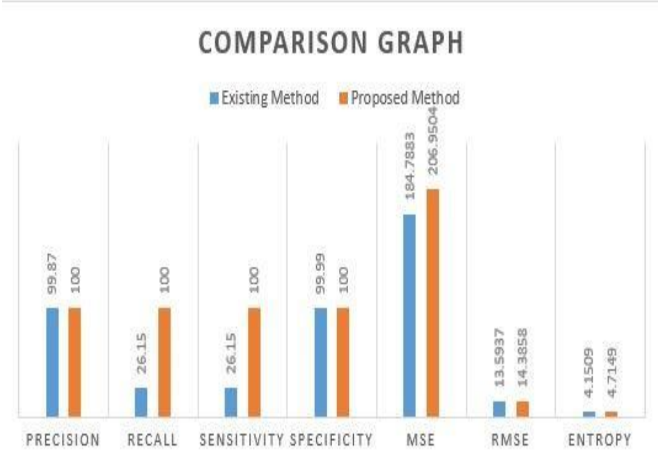

Fig. 8: Measure of Precision, Recall, Sensitivity, Specificity, MSE, RMSEand Entropy.

VI. CONCLUSION

In conclusion, this model produced encouraging outcomes by automating lesion identification and categorization. We are able to accurately locate tumors and classify them into benign and malignant groups by combining CNNs with sophisticated preprocessing approaches. Furthermore, our approach improves diagnostic precision by categorizing malignant tumors into early, intermediate, and metastatic phases and furnishes important details regarding tumor progression. This all-encompassing paradigm not only increases the effectiveness of diagnosis but also emphasizes how deep learning has the ability to revolutionize medical image analysis and pathology evaluation.

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