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COMPREHENSIVE LIVER TUMOR DETECTION AND STAGES CLASSIFICATION USING DEEP LEARNING

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ABSTRACT

This study introduces a deep learning system that automatically identifies and categorizes liver tumors in CT images using convolutional neural networks (CNNs). The approach includes several preprocessing steps such as picture scaling, histogram equalization, bilateral filtering, and K-means segmentation. The CNN is used for binary classification, distinguishing between benign and malignant tumors. When a malignancy is detected, a second CNN-based system categorizes the tumors into Early, Intermediate, and Metastatic stages. This multi-step approach not only automates tumor detection but also provides a finer-grained analysis of malignant cases, offering valuable insights into the progression of liver tumors. The methodology combines advanced image processing techniques with deep learning classification, showcasing a comprehensive framework for efficient and detailed liver tumor analysis in medical imaging. This method simplifies tumor diagnosis and provides important insights into the progression of liver tumors.

Keyword:

CNN

CT images

Deep Learning

Liver Tumors

K – Means Clustering

1. INTRODUCTION

Liver tumors seen on CT imaging are challenging to identify because of the liver's intricate anatomy and the variety of conditions that can cause it to fail. CT imaging is a crucial part of clinical evaluations as it is crucial for identifying and classifying liver tumors. Numerous primary malignancies, such as HCC, benign growths such as cysts or hemangiomas, and other types of liver tumors, can spread and become liver tumors. These tumors can be identified by CT imaging as aberrant masses or lesions with differing densities and levels of contrast-induced uptake compared to the surrounding healthy liver tissue. Accurately categorizing and splitting these abnormalities is almost as difficult as identifying them. Accurately separating the tumor from healthy liver tissue is necessary to determine the tumor's aggressiveness and to choose a treatment plan. Tumors are abnormal tissue lumps that develop when cells begin to proliferate more quickly. The liver can produce both malignant (cancerous) and benign (noncancerous) tumors. Non-cancerous tumors, often known as benign tumors, are generally asymptomatic. Often, an ultrasound, CT, or MRI scan is required before a diagnosis may be made. There are several ways that benign liver tumors might manifest.

Hepatocellular membrane adenomas: There is a connection between this benign tumor and the use of some medications. Numerous of these malignancies are yet unknown. If the adenoma ruptures and begins to bleed into the abdominal cavity, surgery may be necessary. Rarely can malignant tumors start asadenomas.

Hemangioma: A benign tumor made up of many blood arteries that are not quite right. Therapy is not necessary in most cases. Surgery may rarely be required for large hepatic hemangiomas in neonates to prevent blood clotting and heart failure.

Malignant liver tumors are defined as malignant growths within the liver. It may be a primary cancer, which would indicate that the disease originated in the liver. Alternatively, the disease might be a type of metastatic cancer, which happens when a cancer moves from another part of the body to the liver.

HSA (Hemangiosarcoma): It is a mesenchymal tumor that originates from endothelial cells in blood vessels. It is sometimes referred to as a malignant hemangioendothelioma or visceral vascular tumor, in addition to hemangiomas and hemangiosarcoma. Hemangioma is the benign counterpart of hemangiosarcoma.

Hepatoblastoma: Hepatoblastoma is a rare tumor (abnormal tissue growth) that originates in the cells of the liver. For young children, it is the most common type of malignant (cancerous) liver tumor. The majority of hepatoblastoma tumors start in the liver's right lobe.

1. METHODOLOGY

The suggested approach uses a deep learning framework with Convolutional Neural Networks (CNNs) to automatically detect liver tumors in CT images. The initial stages in improving image quality are pre-processing techniques including scaling, histogram equalization, and using a bilateral filter to reduce noise. K-means image-based segmentation improves localization accuracy and offers further refinement. The CNN is then utilized for binary classification in order to distinguish between benign and malignant tumors. A further CNN-based classification method divides cancerous tumors into three phases: premalignant, intermediate, and metastatic. When the CNN concludes that a tumor is malignant, this procedure is followed. With the use of advanced image processing algorithms and deep learning classification, our system can precisely identify tumors in CT scans and offer comprehensive insights into the malignant progression of liver tumors. Following CNN-based classification and preprocessing enables a comprehensive and in-depth analysis of liver pathology.

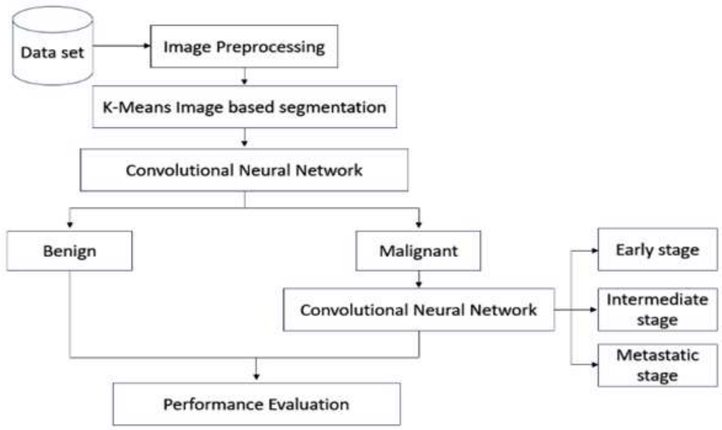


Figure 1: Block Diagram of Proposed Method.

1.1. Image Preprocessing

The main objective of the pre-processing and enhancement step of the image is to change the pixel values in addition to eliminating unnecessary noise and context information. Histogram equalization methods are used to reduce anomalies around the frequency domain and spatial domain descriptions. It greatly enhances the ability of human observers to understand and interpret visual boundaries. Histogram equalization is the most widely used frequency domain technique for improving picture contrast, and it works well with a wide range of image types.

Figure 2: Input Image.

- **Histogram Equalization:** MATLAB's "histeq" function modifies the intensity distribution to improve contrast in pictures. To optimize contrast, it computes a histogram of pixel intensities and redistributes them. By using this technique, details are revealed and visual quality is improved by making darker parts darker and brighter areas brighter. However, it should only be used sparingly because it can also increase anomalies or noise. The cumulative probability function (cdf) must be available for the histogram equalization process to work. By summing up all the probabilities that fall under its domain in equation 1, the cumulative probability function is found.

$$cdf(x) = \sum_{k=-\infty}^{x} p(k) \qquad (1)$$

- **Bilateral filtering of images:** The 'imblatfilt' function in MATLAB is a tool for bilateral filtering in images, which smooths images while preserving edges. It uses two Gaussian filters to compute a weighted average for each pixel, considering spatial distance and intensity differences. This ensures nearby pixels with similar intensity contribute more to the average, maintaining edges and details. The function takes parameters like input image, filter size, and standard deviations to control smoothing and preservation of edges. It is also used for pre-processing and modifying image brightness. Where the value is expanded using the formula Floor (INV – 1) to the closest integer value. Consequently, the histogram equalized the picture "In". To further reduce noise, HE is sent via a bilateral filter.

$$ln^{HE} = floor\left(\left(INV - 1\right) \sum_{he=0}^{ln^{im(i,Q)}} NHS \qquad (2)$$

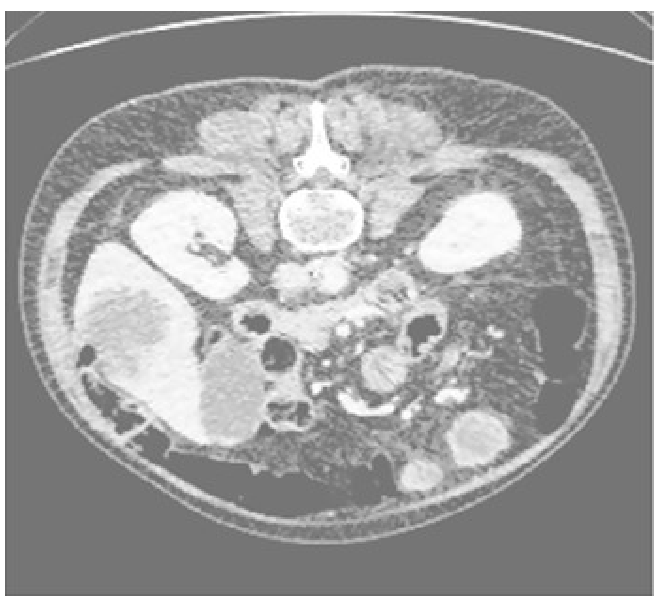


Figure 3: Histogram Equalized Image After Bilateral Filtering.

2.2 K – Means Clustering for Image Segmentation

The K-means clustering-based image segmentation is crucial for early pest detection in crops.

It partitions images into non-overlapping clusters based on pixel similarities, minimizing intra-cluster variance.

This method isolates regions of interest, allowing targeted analysis. Its adaptability helps uncover patterns and structures, contributing to the accuracy of computational intelligence-based pest detection systems.

2.3 Convolution Neural Network

Convolutional Neural Networks (CNNs) are a key component in deep learning, revolutionizing computer vision by extracting intricate patterns from visual data. In MATLAB, CNNs process complex image-based information, mimicking the visual cortex's architecture. They can detect essential details like edges, textures, and shapes, making them useful for image classification, object detection, and segmentation. MATLAB's deep learning toolbox provides pre-defined layers, training functions, and visualization tools, enabling researchers to tailor CNNs to diverse applications. The network architecture varies depending on the application or data, with smaller networks suitable for grayscale data and more complex networks for complex data.

Image Input Layer: The Image Input Layer is essential for integrating image data into deep learning workflows, facilitating diverse dimensions, preprocessing, normalization, and flexibility, and compatible with various neural network architectures.

Convolution 2D Layer: Applying sliding convolutional filters to 2-D input is done using a 2-D convolutional layer. With convolution2dLayer, construct a 2-D convolutional layer. Different parts that make up the convolutional layer are filters and stride, dilated convolution, feature maps, padding, output size, number of neurons, learning parameters, and number of layers.

Batch Normalization Layer: Batch normalization layers normalize a mini-batch of data across observations for each channel, speeding up CNN training and reducing initialization sensitivity. They shift input by a learnable offset and scale factor, enabling larger parameter updates and faster learning.

ReLU Layer: Create a ReLU layer using reluLayer, which performs a threshold operation on input elements, setting any value less than zero to zero. Convolutional and batch normalization layers are typically followed by a nonlinear activation function.

$$f(x) = \begin{cases} x, & x >= 0 \\ 0, & x < 0 \end{cases} \tag{3}$$

Cross Channel Normalization Layer: The cross-channel normalization layer is a channel-wise local response that follows the ReLU activation layer. It replaces each element with a normalized value obtained from neighbouring channels. For each input element x, trainNetwork computes a normalized value x′ using the normalization window.

$$e' = \frac{x}{K + \left(\frac{\alpha * ss}{windowChannelSize}\right)} \tag{4}$$

Max and Average Pooling Layer: Convolutional neural networks use a 2-D max pooling layer and an average pooling layer for down sampling and average pooling. The max pooling layer divides input into rectangular regions, while the average pooling layer calculates the average value. These layers reduce connections and over fitting, with pool size determined by the pool Size argument.

Fully Connected Layer: A fully connected layer connects neurons in previous layers, combining local information to identify larger patterns. For classification, output size equals data set classes, while for regression, it equals response variables. Learning rate and regularization parameters can be adjusted using name-value pair arguments or global training parameters.

Output Layer: A softmax function is applied to the input using a softmax layer. Use SoftMax Layer to create a softmax layer. For classification and weighted classification problems involving mutually exclusive classes, a classification layer calculates the cross-entropy loss. Using classificationLayer, create a layer for classification.A softmax layer and a classification layer typically come after the final fully linked layer in classification issues.

$$y_r(x) = \frac{ex\ \ (a_r(x))}{\sum_{j=1}^{k} exp\ (a_j(x))} \qquad (5)$$

$$0\ \leq y_r \leq 1\ and \sum_{j=1}^{k} y_j = 1$$

3. RESULTSAND ANALYSIS

Every single individual has been examined through CT scans. The sensitivity, accuracy, error rate, and specificity (FN) of diagnostic results are determined by using the values of true positive (TP), true negative (TN), false positive (FP), and false negative (FN). The following expressions (6), (7), (8), (9), and (10) illustrate the formation of these evaluation parameters:

- **Accuracy:** Accuracy is a frequently used performance indicator. It calculates the percentage of accurately identified samples relative to all samples in the dataset.

$$Accuracy = \frac{TP}{TP+TN+FP+FN} \qquad (6)$$

- **Specificity:** Specificity is employed to assess how well a binary classification test performs. It determines the percentage of real negatives in a dataset that are true negative predictions.

$$Specificity = \frac{TN}{TN+FN} \qquad (7)$$

- **Sensitivity:** Sensitivity is the percentage of real positive cases that a classification model accurately detects, also known as the true positive rate.

$$Sensitivity = \frac{TP}{TP+FN} \qquad (8)$$

- **Precision:**Precision is the data that assesses how well a model predicts the positive outcomes. It focuses on the ratio of real positive forecasts to all positive predictions.

$$Precision = \frac{TP}{TP+FP} \qquad (9)$$

- **Recall:** Recall shows how well the model can identify all relevant cases or true positives out of all the real positive instances.

$$Recall = \frac{TP}{TP+} \qquad (10)$$

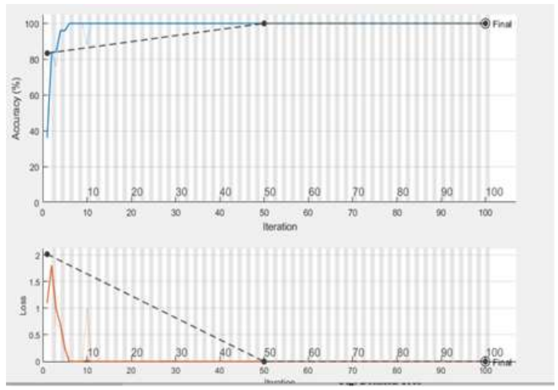
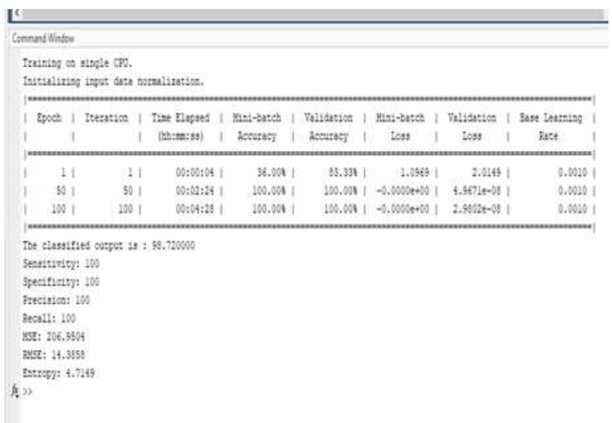


Figure 5.Training Progress.



Command Window

Training on single CPU.
Initializing input data normalization.

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Validation Accuracy	Mini-batch Loss	Validation Loss	Base Learning Rate
1	1	00:00:04	36.00%	83.33%	1.0969	2.0149	0.0010
50	50	00:02:24	100.00%	100.00%	-0.0000e+00	4.9671e-08	0.0010
100	100	00:04:28	100.00%	100.00%	-0.0000e+00	2.9802e-08	0.0010

The classified output is : 98.720000
Sensitivity: 100
Specificity: 100
Precision: 100
Recall: 100
MSE: 206.9504
RMSE: 14.3858
Entropy: 4.7149
>>

Figure 6. Performance Evaluation and Metric Values.

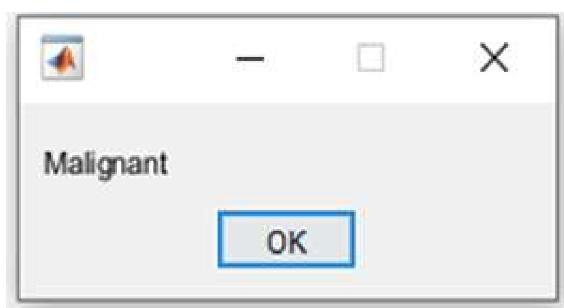


Figure 7: Classification Output.

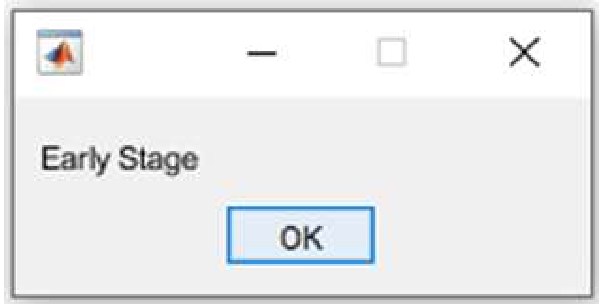


Figure 8: Stages Classification Output.

3. CONCLUSION

In conclusion, automated lesion identification and classification using deep learning-based technology has shown encouraging results in the detection of liver cancers in CT scans. Improved accuracy and reliable tumor localization have been made possible by the combination of CNN with several pre-processing techniques, such as image resizing, histogram equalization, bilateral filtering for noise removal, and K-means image-based segmentation. The CNN classification provides a critical preliminary diagnostic by effectively distinguishing benign from malignant tumors. Furthermore, in instances when malignancy is determined, our methodology enhances the examination by utilizing an additional CNN-based categorization system to group tumors into discrete phases: Early Stage, Intermediate Stage, and Metastatic Stage. This extensive framework demonstrates the potential of deep learning to advance medical image analysis and pathology evaluation by streamlining the diagnosis process and providing thorough insights into the malignancy development of liver tumors.

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