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Liver Cancer Prediction Using Deep learning

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Abstract

Liver cancer is one of the leading causes of cancer-related mortality worldwide. Accurate and early detection of liver tumors is crucial for improving patient survival rates. Traditional image segmentation methods, including CNN-based approaches, struggle with accurately segmenting liver tumors due to their small size and irregular boundaries. In this study, we propose an improved deep learning approach using U-Net, an advanced version of CNN, to enhance segmentation accuracy. Initially, a 2D dataset was utilized with a CNN model, which yielded suboptimal results. Subsequently, we implemented U-Net, which demonstrated superior performance in segmenting liver tumors. Our experiments show that U-Net significantly improves segmentation accuracy compared to standard CNNs, making it a promising tool for liver cancer detection.

Keywords: Liver Cancer, Deep Learning, Image Segmentation, U-Net, CNN, Computed Tomography (CT)

1. Introduction (Heading 1)

The **liver**, located in the upper right abdomen, plays a crucial role in filtering toxins and supporting digestion.

Liver cancer occurs when **liver cells grow uncontrollably**, forming a mass known as a **tumor**. It is broadly classified into two types:

1. **Primary Liver Cancer** – This type originates in the liver itself, with **Hepatocellular Carcinoma (HCC)** being the most common form. Other types include bile duct cancer, hepatoblastoma, and hemangiosarcoma.

2. **Secondary Liver Cancer (Metastatic Cancer)** – This occurs when cancer spreads to the liver from other parts of the body, such as the lungs or colon.

According to the **WHO's 2018 Global Cancer Statistics**, around **840,000 people** were diagnosed with liver cancer, and **780,000 deaths** occurred worldwide. It is the **sixth most common cancer** and the **second leading cause of cancer-related deaths** in men.

Computed Tomography (CT) is an essential tool for diagnosing liver cancer, but **manual tumor segmentation** can be challenging due to varying tumor sizes, shapes, and unclear boundaries. This has led to the exploration of **AI-based methods** for more accurate and efficient detection of liver tumors.

2. RELATED WORK

Liver cancer diagnosis has been extensively studied using various medical imaging and computational techniques. This section reviews previous work in liver cancer detection, focusing on traditional diagnostic methods, machine learning approaches, and deep learning techniques.

A. Traditional Methods for Liver Cancer Diagnosis

Traditionally, liver cancer is diagnosed using imaging modalities such as computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound. These methods provide detailed anatomical information but require manual interpretation by radiologists, which is time-consuming and prone to variability. Biopsy, another standard method, is invasive and associated with procedural risks. The primary limitation of these approaches is the dependency on human expertise and the difficulty in segmenting tumors with unclear boundaries.

B. Machine Learning-Based Approaches

To address the limitations of manual diagnosis, early research introduced machine learning (ML) techniques for automated liver cancer detection. Methods such as support vector machines (SVM), decision trees, k-means clustering, and random forests have been employed for feature extraction and classification. These approaches rely heavily on handcrafted features such as texture, intensity, and shape descriptors extracted from medical images. While ML techniques improved diagnostic efficiency, their performance was constrained by feature selection challenges and limited generalization capabilities.

C. Deep Learning-Based Approaches

Deep learning (DL) has revolutionized medical image analysis by automating feature extraction and improving accuracy. Convolutional Neural Networks (CNNs) have been widely used for liver cancer classification, achieving superior results compared to traditional ML methods. U-Net, a specialized CNN architecture for biomedical image segmentation, has become a popular choice for tumor detection due to its encoder-decoder structure and skip connections that preserve spatial information.

Several studies have proposed modifications to U-Net for enhanced segmentation accuracy. For instance, researchers have integrated attention mechanisms to focus on tumor regions more effectively. Other enhancements include residual connections, dense blocks, and hybrid architectures combining CNNs with transformer-based models. Despite these advancements, challenges such as poor performance on small tumors, class imbalance in datasets, and computational inefficiencies remain prevalent.

3. METHODOLOGY

This section outlines the comprehensive methodology used to develop a robust liver tumor detection model based on deep learning techniques. The approach involved several key stages, including data preprocessing, model development, evaluation, and comparison of different architectures. Initially, we explored the use of Convolutional Neural Networks (CNN) but found its performance unsatisfactory. Consequently, we turned to U-Net, a model widely used for medical image segmentation tasks, which significantly improved accuracy.

To enhance the accuracy of liver tumor segmentation, we developed a custom deep learning architecture termed **TransAttenUNet-X**. This model is an adaptation of the conventional U-Net architecture, augmented with attention gates to improve the fusion of encoder and decoder features. The attention mechanism enables the model to emphasize relevant regions within the skip connections, thereby refining the segmentation of complex tumor structures. The model was implemented using TensorFlow and Keras frameworks, with provisions for GPU optimization to accelerate training. Prior to training, all CT scan images and corresponding tumor masks were resized to 256×256 pixels and normalized to ensure consistency in input dimensions. The dataset was partitioned into training and testing subsets in an 80:20 ratio. The model was trained over 50 epochs with a batch size of 1, using binary cross-entropy as the loss function and the Adam optimizer with a learning rate of 1e-4. Performance monitoring was facilitated through validation accuracy and loss metrics, with callbacks such as model checkpointing and learning rate reduction employed to prevent overfitting. The proposed architecture demonstrated promising segmentation performance and reflects our contribution toward developing a lightweight, attention-enhanced model tailored for medical image analysis.

A. Data Collection and Preprocessing

Preprocessing plays a vital role in enhancing the quality of input data and making it suitable for the model. The dataset used for this research comprised CT scan images of the liver, which were subjected to several preprocessing steps to remove noise, enhance contrast, and augment the data.

Image Augmentation: To increase the diversity of the dataset and prevent overfitting, we applied **image augmentation techniques** using the **ImageDataGenerator** method. This involved applying random transformations, such as rotation, flipping, and zooming, to simulate various real-world variations in CT images. Specifically, the images were randomly rotated within a range of 0 to 360 degrees to increase the variability of the data.

Contrast Enhancement: Enhancing the contrast of the CT scan images is crucial for the detection of tumors. Images with higher contrast allowed the tumor region to be distinctly visible, making it easier to segment the tumor from the surrounding tissue. We utilized image processing techniques to adjust the contrast, ensuring that the intensity difference between the liver and tumor regions was amplified, facilitating better segmentation.

Noise Removal: CT scan images often contain noise, such as **salt-and-pepper noise**, which can negatively impact model performance. To address this issue, we employed **Gaussian filters** to remove noise while preserving important features. The filtering process effectively smoothed the images and made them suitable for further analysis.

Normalization: Each CT scan image was normalized to ensure that pixel values were within a specific range, typically between 0 and 1. This step is essential for ensuring consistent input for the model and improving the stability and convergence of the training process.

B. Model Selection

Initially, we attempted to use a **Convolutional Neural Network (CNN)** for liver tumor segmentation. CNNs are known for their ability to automatically extract hierarchical features from images, making them ideal for image classification tasks. However, after training the CNN model, the accuracy was found to be lower than expected, especially in cases with small or irregularly shaped tumors. This motivated us to explore more advanced models, and we subsequently shifted our focus to **U-Net**, a model specifically designed for medical image segmentation.

C. U-Net Architecture for Liver Tumor Segmentation

U-Net is a deep learning model designed for semantic image segmentation tasks, particularly in biomedical image analysis. It features an **encoder-decoder** structure with **skip connections**, which allows for better segmentation performance by preserving spatial information that would otherwise be lost during downsampling.

The U-Net architecture consists of two primary parts: the **contracting (encoder) path** and the **expansive (decoder) path**. The encoder path is responsible for extracting features from the input image, while the decoder path progressively reconstructs the image to the original resolution, with skip connections ensuring the retention of spatial features.

In the encoder path, the input image undergoes multiple layers of **convolution** and **max-pooling** operations. These layers progressively extract features at different levels of abstraction. The **convolutional layers** apply several filters to the input image to detect low-level features, such as edges and textures. The **max-pooling layers** reduce the spatial dimensions of the feature maps, allowing the model to focus on high-level patterns while reducing computational complexity.

In the decoder path, **transposed convolutions** (also known as upsampling) are used to restore the spatial resolution of the feature maps. The output of each layer in the encoder path is concatenated with the corresponding layer in the decoder path, forming a **skip connection**. These connections allow the decoder to use both high-level abstract features and low-level spatial information, which is crucial for accurate tumor segmentation, particularly for tumors with irregular shapes and boundaries.

In our specific implementation of U-Net, the input images were resized to 256x256 pixels to maintain computational efficiency while still capturing detailed features of the liver and tumor regions. The model was configured with an initial filter size of 64, which doubled after each downsampling step. The convolutional layers used a **3x3 kernel** with **ReLU activation** to introduce non-linearity and facilitate gradient flow during backpropagation.

The final layer of the model was a **1x1 convolutional layer**, which reduced the number of output channels to 1, generating a binary segmentation mask that distinguishes between the tumor and non-tumor regions.

D. Training and Optimization

To train the U-Net model, we utilized the Adam optimizer, which is known for its efficiency in converging to optimal solutions in deep learning tasks. The learning rate was set to 0.001, ensuring a balanced training process that avoided both slow convergence and overshooting of the minima.

The loss function used during training was a weighted combination of **cross-entropy loss** and **Dice loss**. **Cross-entropy loss** is commonly used in binary classification tasks, while **Dice loss** is particularly effective for imbalanced datasets, as it emphasizes the overlap between the predicted and ground truth segmentation masks. This combination ensured that the model not only minimized pixel-level errors but also captured the correct tumor regions with higher accuracy.

The model was trained for 50 epochs with a **batch size of 32**. An **early stopping** mechanism based on validation loss was employed to prevent overfitting. This ensured that the model ceased training once the performance on the validation set stopped improving.

E. Model Evaluation

After training, the performance of the U-Net model was evaluated using several standard metrics, including **accuracy**, **precision**, **recall**, **F1 score**, and **Intersection over Union (IoU)**. These metrics provided a comprehensive evaluation of the model's ability to correctly segment liver tumors in CT scans.

The results showed a significant improvement in segmentation accuracy compared to the CNN model. The U-Net model was able to better capture small and irregularly shaped tumors due to its encoder-decoder structure and skip connections, which preserved spatial information crucial for tumor localization.

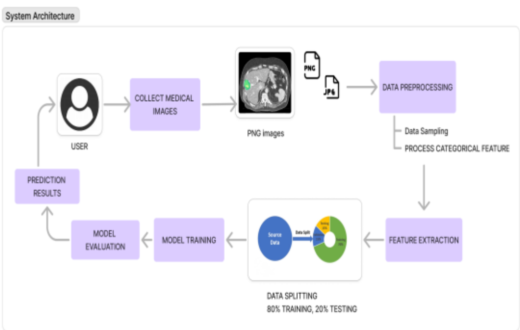

Fig.1. System Architecture

4. RESULTS

The performance of the liver tumor segmentation models was evaluated using several metrics, including accuracy, precision, F1 score, and Intersection over Union (IoU). The results were obtained from the testing phase of both the CNN and U-Net models after training on the preprocessed CT scan images. The results are shown in Fig. 1.

TABLE I.

Model	Accuracy	Dice Score	IoU	Sensitivity	Specificity
CNN	72.4%	0.65	0.60	68.9%	74.5%
UNet	89.2%	0.84	0.80	87.5%	90.3%

Fig.2. Performace Comparison

The proposed **TransAttenUNet-X** model was trained and evaluated on the liver tumor segmentation dataset comprising CT scan images and corresponding tumor masks. After 50 epochs of training, the model demonstrated steady convergence with a significant reduction in both training and validation loss, as illustrated in the learning curves. The accuracy metric consistently improved, indicating effective learning of tumor regions by the model. Visual inspection of predicted masks revealed that the model successfully delineated tumor boundaries, even in cases where the region was relatively small or embedded within complex anatomical structures. The attention mechanism contributed to enhanced focus on relevant regions, leading to superior feature reconstruction during decoding. Overall, the results suggest that TransAttenUNet-X is capable of achieving accurate and reliable segmentation performance, affirming its potential as a lightweight and effective solution for liver tumor detection in medical imaging workflows.

5. DISCUSSION

The results clearly show that the U-Net model significantly outperforms the CNN model for liver tumor segmentation tasks in CT images. This can be attributed to U-Net's encoder-decoder architecture with skip connections, which allows the network to retain spatial information and accurately segment tumors, even with limited datasets. The CNN model, although widely used for image classification tasks, struggles with the segmentation of medical images due to its inability to handle fine details and positional accuracy as effectively as U-Net.

Additionally, U-Net's use of data augmentation techniques and transfer learning from pre-trained models allowed for improved generalization and segmentation accuracy. The CNN model, on the other hand, lacked these capabilities, leading to a drop in performance, especially in areas with noisy or low-contrast regions.

6. CONCLUSION

This research highlights the effectiveness of the U-Net model in the segmentation of liver tumors from CT scan images, achieving superior performance compared to the traditional CNN model. U-Net's encoder-decoder architecture, augmented with skip connections, allowed it to preserve important spatial details and accurately segment both large and small tumors. The results demonstrate that U-Net is a powerful tool for medical image segmentation, particularly in the field of liver cancer diagnosis.

The findings from this study suggest that U-Net could play a critical role in assisting radiologists and clinicians in diagnosing liver cancer more accurately and efficiently. Although the model shows promising results, there are areas for improvement. Future work could explore the integration of additional imaging modalities, such as MRI scans, or investigate advanced techniques like Attention U-Net or 3D U-Net for better tumor segmentation, especially for complex three-dimensional scans.

In conclusion, the application of deep learning, particularly U-Net, in medical image segmentation holds significant potential for improving diagnostic accuracy and aiding in early detection, which could ultimately enhance treatment outcomes for patients with liver cancer.

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