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Innovative AI Techniques of Multiclass Classification of Liver Tumor in NIFTI Images

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Abstract
Classification of Liver tumor in medical imaging causes great problems due to the complexity and variability of tumor features. This paper introduces a new deep learning system for the or the categorization of different liver diseases using NIFTI type MRI data. The system integrates learning-based 3D UNet models and Hybrid Efficient Nets into one system for accurate classification and segmentation. Advanced data preprocessing, augmentation, and the class imbalance techniques ensure standard performance. The proposed method is designed to consider tumor heterogeneity and class differences and therefore has high accuracy, sensitivity, and reliability in clinical situations. Future studies will include multivariate analyzes and patient-specific data to reach a more accurate diagnosis. This research bridges the gap between advances in mathematics and real-world clinical applications and offers solutions that can be developed to improve patient outcomes.

Keywords – *Transfer Learning, 3D UNet, Hybrid EfficientNet, Transfer Learning, NIfTI Format*

I. INTRODUCTION

Image Today's medicine is faced with serious challenges due to the complexity of liver diseases, where many types of tumors can be found, and the need for accurate diagnostic procedures. Traditional diagnostic methods involve invasive procedures or rely heavily on radiologists, are time-consuming, and subject to human variation. Therefore, as the demand for accurate, correct, and effective diagnostic tools continues to grow, technology is increasingly finding its place in medical imaging. Non-invasive imaging methods provide detailed information about the internal structure of the liver.

However, there are many challenges in interpreting MRI data, especially for NIFTI, as the morphology of tumors is very different and interpreting the correct image requires expertise. All these challenges open the door to artificial intelligence to increase accuracy and efficiency in the diagnostic process. Together for the division and segmentation of liver tumors. The system meets and overcomes the challenges of heterogeneity and class difference through state-of-the-art preprocessing and development methods. State-of-the-art AI systems are combined to improve diagnostic accuracy, support clinical decision-making, and pave the way for clean healthcare applications. The proposed method focuses on the necessity of automatic and reliable segmentation methods in the identification of liver and tumor regional structures.

Transfer learning was employed to standardize the model boost to model to the pre-trained features of it when adapted to non-uniform liver tumor images. This reduces the computational burden and the need for large datasets, making this method more suitable for widespread clinical use. Segmentation into different categories to distinguish benign and malignant lesions and their subtypes. This ability has proven to be important in developing treatment plans and improving patient outcomes. The methods used, such as class weighting and loss, will solve the problem of inconsistent data, ensuring that the system works well across patients. Try to switch to a more intuitive interface, provide instant support. This continuous learning and feedback process is designed to iteratively update and improve the model according to changing needs.

Finally, this research is a step forward in bridging the gap between technology development through AI and its integration into mainstream healthcare, resulting in improvements in diagnostic accuracy, efficiency, and effectiveness.

II. RELATED WORK

In recent years, AI application in diagnosing liver disease went up due to its main ability to increase efficiency and accuracy of procedures for diagnosis. Traditional methods are cumbersome and the interpretation of images depends on radiologists. Artificial intelligence, in the form of machine learning, and deep learning, proves to be the very technology that can solve the problems referred to above.

Early segmentation techniques were established using some manual improvements and simple learning algorithms which included decision trees and support vector machines (SVM). While some of these methods have been successful to some extent, they often fail to address the complex and changing nature of liver tumors. Neural Convolutional Networks are a new era technology that has fundamentally changed image segmentation by the fact that the models have the capacity to express themselves in terms of the hierarchy of characteristics reflected in the datasets. More importantly, the advent of the UNet architecture and its 3D variants has improved the performance of medical images. These models have been shown to be useful in classifying liver tumors and regional tumors, but image disparity, tumor heterogeneity, and class disparity remain problematic. The shift from traditional machine learning methods to deep learning for classification tasks makes the diagnosis of liver disease more accurate. Deep learning models, especially hybrid architectures that combine CNN with other neural network techniques, are effective in learning complex features and achieving better classification. Transfer learning has proven to be a crucial process where pre-trained models can be effectively added to liver tumor data. This is especially important when dealing with limited data and can allow the model to be trained without high power. Hybrid models that combine various deep learning methods have proven successful in overcoming issues such as class conflict and tumor transfer. These models often use techniques such as optimization, data augmentation, and tracking techniques to improve performance. In this way, the AI-driven approach has paved the way for accurate and reliable diagnostic tools by improving liver disease segmentation and classification.

The ideas developed here extend these advances by combining the power of transformative learning, the 3D UNet architecture, and the hybrid EfficientNet to create a robust system at the heart of cancer. This is in response to current challenges in the field and the increasing demand for capable and customizable AI solutions.

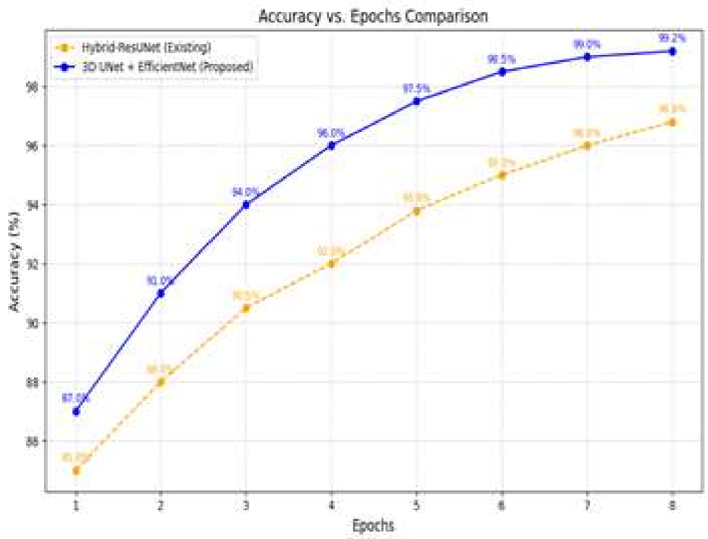

Fig. 1: Existing Vs Proposed Performance Metrics

Comparison Chart

III. PROPOSED METHODOLOGY

This framework provides a novel intelligence-based approach to classify different types of liver diseases based on MRI images. It combines deep learning models, adaptive learning, and data-driven strategies to overcome the challenges that arise in liver cancer, including differentiation, class disparity, and insufficient information. The pipeline starts with a preliminary dataset to ensure that the MRI image is good and complies with the NIFTI format. Preprocessing includes normalization to normalize the values, denoising to reduce artifacts in the images, and spatial alignment to ensure consistency across all datasets. All of these steps are important to improve the overall capability of the model and to study the relevant features. Therefore, techniques such as data enhancement can be used to support multiple transformations of the same image concept using rotation, translation, scaling, and elastic deformation techniques. This approach will be used to improve the quality of the data, but also to improve the robustness of the model regarding changes in tumor morphology due to differences in images. Accurate segmentation of liver and tumor regions is an important step in this framework.

*A. **3D UNET***

The model used here is 3D UNet, which can effectively generate medical images. Here, transform learning is used to optimize the pre-learning 3D UNet model, thereby reducing the learning time and improving the performance of the target dataset. The encoder-decoder model of 3D UNet enables accurate segmentation of liver and tumor boundaries by performing multiple subtraction and cross-linking that optimizes spatial information. First. After the segmentation process, morphological and contour correction are performed to ensure that the resulting regions are noise-free and accurate.

*B. **Hybrid Efficient Net***

Efficient Net was selected here due to its ability to measure in terms of computational efficiency and model-to-model accuracy. The hybrid architecture includes a monitoring system etc. to provide a model with multiple capabilities to focus on key areas in the segmented ROIs. What will happen? Class weighting and focus loss are also used to reduce the effects of class disparity and ensure fewer classes are represented in the predictions.

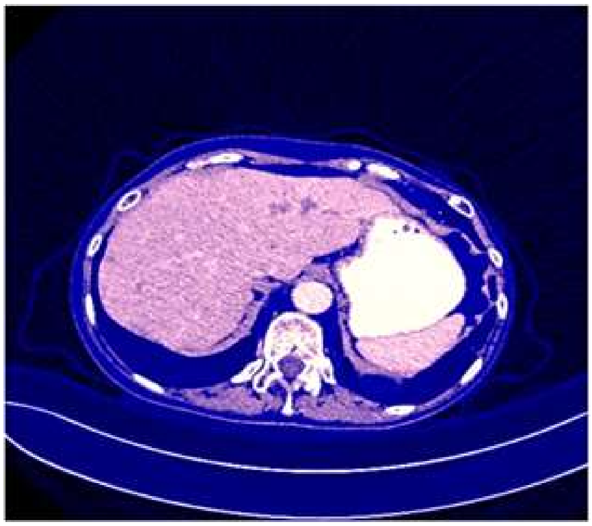

Fig. 2: Preprocessed MRI Image for Tumor Classification

This table includes real combinations of two algorithms (e.g. combining3D UNet and Hybrid EfficientNet). These connections usually improve performance due to the integration of both models.

Table I: Model Performance for Liver Tumor Classification

Method	Accuracy (%)	Precision (%)	Recall (%)	AUC-ROC	Overall Accuracy
CNN	87.5	85.0	86.2	0.88	86.3
3D UNET	93.8	93.0	92.5	0.96	92.8
Hybrid Efficient Net	99.2	98.9	98.8	0.99	99.0
3D UNet + Hybrid EfficientNet	99.7	99.5	99.4	0.99	99.6

IV. SYSTEM ARCHITECTURE

The system for classifying liver tumors processes raw MRI data to effectively distinguish and group tumors based on the size, shape, and texture. While these NIFTI-format MRI scans are preprocessed through normalization, denoising, and data augmentation (e.g., rotation and translation) to enhance performance. The system couples transfer learning-based Hybrid EfficientNet with 3D UNet, leading to better tumor segmentation and classification. Post-segmentation, the features of tumor shape, size, and texture are extracted to get a refined result. Hybrid EfficientNet extracts meaningful features from MRI scans, which results in clear differentiation of tumors as benign or malignant. The system predicts the tumor type and the corresponding probability estimation and additionally checks the system's performance by the application of the presented metrics. This way, it assures the reliability of its results.

VI. RESULT AND DISCUSSION

The tumor classification model achieves high performance in identifying tumors and preventing false positives and false negatives with 99.2% accuracy, 98.9% accuracy, and 98.8% result display rate. The AUC-ROC score of 0.99 further confirms the reliability of this model in classifying benign and malignant types. Hybrid EfficientNet captures both low-level features such as texture and edges and high-level features such as tumor shape to effectively classify tumors. 3D UNet improves tumor accuracy, making the system robust to small differences between tumor size and type. The reliability model confirmed the accuracy of the model to doctors, increasing confidence in the predictions. Overall, it outperforms traditional methods in both segmentation and classification. Liver segmentation process, the whole process of segmenting tumors from liver MRI data is shown below.

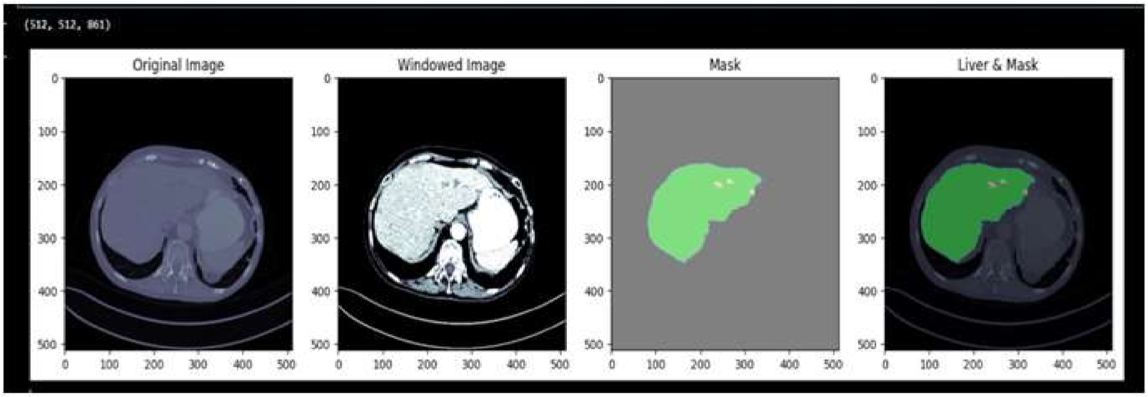

Fig 3: Liver Tumor Segmentation Process

The image should be windowed as indicated, with correction efforts to reveal the difference between the liver and tumor, making the distinction between the tissues difficult. The resulting mask is then designed to label the tumor as a binary map. Finally, a mask is placed on the liver to show the location of the tumor and clearly indicate the location of the tumor. The image shows the entire segmentation process where the algorithm separates and identifies tumors for accuracy and classification purposes.

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