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Deep Learning Approach in Detecting Liver Cancer from Medical Images with Explainable AI (XAI) Technique

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***Abstract*—Liver cancer is a pressing global health issue often diagnosed at advanced stages, leading to poor prognosis. Artificial intelligence (AI) has shown promise in improving liver cancer detection from medical images. However, the lack of interpretability in AI models hampers their clinical adop-tion. This research proposes a novel approach that combines U-Net, a deep learning model, with LIME(Local Interpretable Model-agnostic Explanations), Which is an explainable AI technique, to enhance liver cancer detection. The proposed model aims to provide explanations for its predictions,helping physicians comprehend and accept the decisions made by the model.The findings support the development of AI in medical diagnostics by demonstrating the efficacy of the suggested method in identifying liver cancer and offering insightful information about the decision-making process.**

Key words—Liver cancer, Diagnostic imaging, Unet, LIME,Explainable Artificial Intelligence (XAI), Machine learning, Medical images, Transparency, Interpretability, Deep learning, Image segmentation, Explainability methods.

I. INTRODUCTION

Being the sixth most frequent cancer and the fourth main cause of cancer-related deaths globally, liver cancer poses a serious threat to global health. Since early detection enables prompt intervention and treatment, liver cancer detection is essential for improving patient outcomes. Liver cancer diagnosis and follow-up are greatly aided by medical imaging techniques including magnetic resonance imaging (MRI) and computed tomography (CT). However, the in-terpretation of these images can be complex and subjective, leading to variability in diagnoses among radiologists.

In the field of medical imaging, artificial intelligence (AI) has become a potent instrument with the potential to increase the precision and effectiveness of cancers diagno-sis. Deep learning, a subset of AI, has shown particularly promising results in image analysis tasks.Convolutional neural networks (CNNs), one type of deep learning model, have been effectively used to diagnose a variety of malig-nancies, including liver cancer, from medical images. Despite their success, Deeplearning model often lacks of transparency, interpretability, which are critical for their acceptance and adoption in clinical practice. The goal of explainable AI (XAI) approaches is

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to overcome this constraint by offering justifications for the choices that AI models make. XAI can contribute to increased confidence in AI systems and make it easier for them to be integrated into healthcare workflows by making AI more understand-able and transparent.

In this Research paper, we propose a novel approach that combines the power of the deep learning with XAI to improve the detection of liver cancer from medical images. Specifically, we use U-Net, a deep learning model com-monly used for image segmentation tasks, in conjunction with LIME(Local Interpretable Models-agnostic Explana-tion), an XAI techniques that provides feature importance scores for individual predictions. Our proposed approach aims to not only enhance the accuracy of liver cancer de-tection but also provide clinicians with meaningful insights into the features driving the model's predictions. We believe that our approach has their potential to significantly impact in the field of the liver cancer detection and contribute to the broader goal of leveraging AI for improving healthcare outcomes

II. Literature Review

The Research paper [10]tells as the different types of liver cancers such as:

1) Hepatocellular Carcinoma (HCC): it stand as predomi nant form of primary liver cancers, accounting for the ma-jority of cases. Emerging primarily from hepatocytes, the main functional cells of the liver, HCC is often associated with the liver diseases such as cirrhosis and chronic hep-atitis B or C infections. Hepatocellular carcinoma (HCC), it is the most common type worldwide. [19]

2) Intrahepatic Cholangiocarcinoma (ICC): Intrahepatic Cholangiocarcinoma (ICC)orginates in the bile duct within the liver. This rare but aggressive form of liver cancer poses diagnostic challenges due to its location and may present with symptoms similar to other liver conditions.ICC accounts for 10–20% of all primary liver tumors and 8–10% of cholangiocarcinomas. Globally, there is still a significant geographic variance in the prevalence of ICC. [9]

3) Hepatoblastoma: While comparatively rare, Hepatoblas toma is one of the most commonly primary malignant liver tumor in childrens This aggressive tumor originates in the immature liver cells and typically occurs in children under the age of five. Understanding the distinct characteristics of hepatoblastoma, including genetic predispositions and risk factors, is vital for tailoring effective treatment approaches for pediatric pa tients.A extremely high survival rate of between 70 and 80% is linked to HB. Nevertheless, it was less than 30% before to the introduction of chemotherapy (CHT). [5], [7]

The research paper [17] proposes an innovative approach for liver tumor detection using the synergy of deep learning base segmentations and Coot Extreme Learning Model (ELM). Using CT scans from the publicly available 3D-IRCADb1 dataset, which contains more than 200 patient-annotated liver and tumor segments, the method starts with Gabor filters that extract pixel-level texture and edge information. Three ELM classifiers trained on different Gabor filter responses trigger liver segmentation. Next, a refined liver image is obtained using a modified U-Net ar-chitecture, where the user interacts to refine the boundaries and geodesic distance coding improves the accuracy. Tumor segmentation is achieved using individual ELM classifiers trained on different feature sets derived from the liver region, including intensity, texture, and edge infor mation. The combined set of features from the segmentation and classification steps is then used to train the Coot ELM to discriminate between normal and diseased CT images.

In particular, this proposed method shows convincing re-sults, achieving dice score 0.96 for theliver segmentations, 0.82 for tumor segmentations, andan overall accuracy of 89.5% which exceeds existing approaches [17]. The study highlights the use of the 3D-IRCADb1 dataset for realistic evaluations and highlights advantages such as efficiency, user interaction and robust generalizability. Recognizing the limitations associated with image quality sensitivity, the study recommends future work involving validation of larger data sets and the inclu sion of additional modalities such as MRI to improve tumor detection accuracy. In conclusion, this comprehensive study provides a promising deep learning framework for liver tumor detection, paving the way for potential clinical applications that await further validation and research.The following fig.1 [17]showing a working flow of their coot Extreme Learning Model.

The research paper [15] presents a new approach for automatic liver cancer detection by combining pre-trained deep learning model with custom algorithms. Method in-volves a collections and preprocessing of CT scan im-ages from the Cancer Image Archive (CIA) using high-scaling techniques to increase the diversity of the data. Hybrid feature extraction uses pre-trained convolutional neural networks (ResNet-50, VGG16 and DenseNet121) whose features are combined and processed using a custom Multiscale Spatial Pyramid Pooling (MSPP) module. A Support Vector Machine classifiers predicts the presence of the cancers, and an attention-guided region proposal net-work (AG-RPN) locates potential tumor regions. Accurate predictions are provided

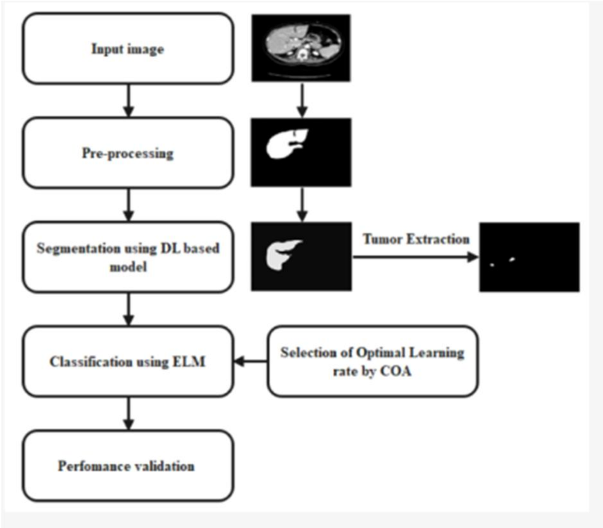

Fig. 1. Working Flow of coot Extreme Learning Model

by refinement using non-maximum damping (NMS) and validation based on ground-truth an-notations. The study uses 443 CIAs for trainings, 50 for the validations and 50 for thetesting.The suggested approach for cancer detection yields an AUC of 0.98, a sensitivity of 88.9% and a tumor site specificity of 97.2% which outperforms existing methods. Highlighting the advantages of pre-trained models and the efficiency of the AG-RPN module, the results show the potential to help radiologists in early diagnosis of liver cancer. While acknowledging the limitations and recommending future work involving larger data sets and other imaging modalities, this study offers a promising way to improve patient outcomes through early detection.

The Research paper [2] propose TS-CNN, a three-layer architecture that exploits the strengths of both global and local features. Expanding upon earlier research that highlighted the ”black box” aspect of deep learning algorithms, they integrate an attention branch along with the global and fusion branches. This attentional mechanism selectively focuses on important areas and provides interpretation through visualization. Using various pre-trained CNNs, the authors assessed TS-CNN on the PAD-UFES-20 skin lesion dataset. (Dense Net- 121, Inceptions, Xceptions, ResNet 50) with global and local branch. GradCAM and visibility map are used for visualization, revealing model inferences. The results show competitive accuracy compared to existing methods, reaching 92.24% with DenseNet-121, while providing interpretable attention maps for each prediction. This research paves the way for interpretable deep learning in medical image analysis, which can increase confidence and understanding in AI-based diagnosis.

TheResearch paper [12]compares the segmentations of liver using the U-Net and ResNet50 techniques and presents the findings of their experiments. The authors have used a dataset to evaluate and compare the performance of these two methods using various evaluation metrics such as overall accuracy, true positive rates, true negative rates, intersection over union, precision,F1 scores. Result of the study shows that U-Net model has outperformed ResNet50 in terms of segmentation performance and achieved better results based on the evaluation metrics. The paper also provides a detailed methodology used in the study, such as the loss function curve for the U- Net model, which has converged after 100 training cycles. Overall, the Paper presents comprehensive information on the liver segmentation study using U-Net and ResNet50 and their experimental results.

In the Research paper [13]describe an innovative approach to detect liver tumor using medical imaging, starting with extensive CT image pre-processing and feature extraction using Gaborfilter. Three Extreme Learning Machine (ELM) classifier contribute to liver segmentations followed by refinement using a modified U-Net architecture with geodesic distance coding. Tumor segmentation use sophisticated liver mask and individual ELM classifier. The research uses publicly available 3D-IRCADb1 dataset and achieves impressive result, highlighting synergy between traditional and deep learning technique. Limitation include sensitivity to image quality, suggesting future work with additional modalities such as MR to improve accuracy. The study highlight the promising clinical applications and advances in patient care made possible by AI-based liver tumor detections. In addition, a parallel study focuses on detection of liver tumor using the KMC algorithm and highlights the accuracy and sensitivity of AI-based medical imagingin the identification and management of hepatic tumors. Together, these studies demonstrate the effectiveness of artificial intelligence in revolutionizingthe identification and management of hepatic tumors using advanced medical imaging techniques.

The research paper [18] effectiveness and trustworthiness of autonomous systems, developed with the goal of creating intelligent agents capable of perceiving, learning, deciding, andacting independently, hinge on explainability of models.The concept of Explainable AI (XAI) has recently emerged to address the need for understanding the decision-making processes of Machine Learning/Deep Learning (ML/DL) algorithms. XAI serves as a subset of AI dedicated to applying methods and techniques that render the results of Artificial Intelligence (AI) human interpretable. Particularly in applications requiring swift deployment, the incorporation of domain knowledge through XAI can play a pivotal role in selecting models, ensuring that the deployed AI model focuses on pertinent features for accurate classification. This, in turn, enhances user confidence in the outcomes produced by the AI model.

This research paper [11]endeavors to enhance the ac-curacy and interpretability of liver tumor segmentation in medical images, utilizing a U-Net architecture within con-text of deep learning. A significance of accurate liver tumor segmentation lies in its pivotal role in disease diagnosis and pre-surgical planning. The study involves a comprehensive performances analysis of MRI scan and CT scan obtained from diverse patients sources, both offline and online. An encoder-decoder structure using rectified linear unit (RELU) functions as the activation functions is used in the proposed U-Net architecture. To optimize accuracy, various operators are experimented with, ultimately selecting the max-pooling operation, resulting in an impressive accuracy of 98.5%. The researcher employed the following fig. 2 [11] architecture for the 2.5-dimensional image.

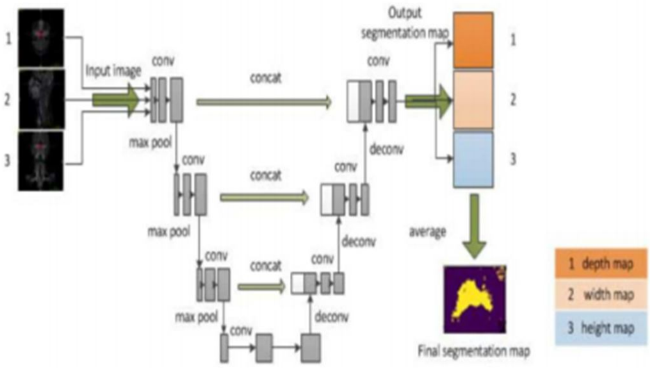

Fig. 2. U-Net Architecture

III. METHODOLOGY

A. Dataset

The dataset used in this study comprises CT scans of hepatocellular carcinoma (HCC) with arterial and portal phases in the abdomen.We utilized a dataset of 130 CT scans for liver and tumor segmentation, obtained from the LiTS – Liver Tumor Segmentation Challenge (LiTS17) [4].This dataset is valuable for our research as it provides detailed imaging information necessary for employing deep learning models for the investigation and detection of liver cancer.

B. Deep Learning Model

We use the U-Net architecture,a proven deep learning model for tasks involving the segmentation of medical images.An encoder-decoder with bypass links is used in the U-Net architecture to effectively capture local and global functionalities. A certain U-Net configuration (e.g. number of layers, filter sizes) is optimized based on available datasets and computational resources. The dice drop func-tion, commonly used in segmentation tasks, is used during training to promote pixel-by-pixel accuracy. To optimize model performance, we use the Adam optimizer with care-fully selected hyperparameters (learning, set size, epochs). In addition, we can explore modifications of the U-Net ar-chitecture that are specifically designed to be interpretable, such as to incorporate attention mechanisms.The U-Net architecture uses bypass connections, which allows low-level and high-level functions to be efficiently combined over narrowing and widening paths. This facilitates the storage of spatial data and allows the model to capture both local details and global context, improving segmentation accuracy.

C. Explainable AI Technique

In our project, we've integrated Lime for explainable AI, adding a layer of interpretability to our system. Our U-Net model serves as the primary predictive engine, tasked with discerning the presence of liver tumors. Upon detection of a tumor, the U-Net model generates an output, which seamlessly feeds into Lime for interpretation. Lime steps in to shed light on the decision-making process, providing insights into why the model made a particular prediction. This approach not only enhances the transparency of our AI system but also empowers clinicians and stakeholders with valuable information regarding tumor identification, fostering trust and facilitating informed decision-making in medical diagnoses. Their is an another explainable ai method called SHAP (SHapley Additive exPlanations): The goal of the SHAP value is to assign each feature's contribu-tion to the predictions. It is derived from cooperative game theory. In order to better understand how each input feature affects the model's output, SHAP values offer a consistent measure of feature relevance. [6]. LIME It is not dependent on any particular model and may be applied to construct regression and classification models for any kind of data, including tabular, picture, semantic, and other types. Kalko takes an input image that is supplied to models, turns it into super-pixels, makes a variety of perturbations to the image, and then predicts for every sample. Base on the prediction, an equivalent weight is assigned to the superpixels of all samples. [14] In the realm of explainable artificial intelligence (XAI), explanations are categorized into post hoc models [3] and Intrinsics models [16]. Post hoc interpretation strategies, like layer-wise relevance prop-agation, class activation mapping, and backpropagation, analyze both original and additional models to provide explanations for trained models. Intrinsics interpretability allows modification of a model's structure or components, while post hoc models analyze interpretable data collected by external pattern analysis methods. XAI models can be model-specific [1] or model-agnostic, depend- ing on their applicability to other model types. Annotation areas in XAI can be global or local [8]z, focusing on specific factors influencing decisions or gaining insight into the model's behavior.

D. Our Proposed Architecture

The preprocessed medical image data is fed into the U-Net model, which is tasked with segmenting the liver and any tumors present within it from the image. Through training on this data, the model learns to distinguish be-tween images with and without liver tumors. If a tumor is detected, the model's output is then passed to the LIME(Local Interpretable Model-agnostic Explanations) model for further analysis. The integration of Lime for the U-Net model's predictions enhances interpretability by elucidating the reasoning behind each prediction, offering insightful information about the decision-making process and promoting a better comprehension of the existence of liver tumors.Figure 3 illustrates how the suggested model operates.

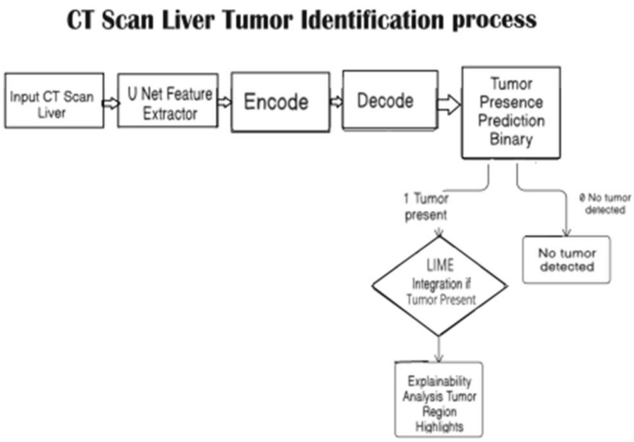

Fig. 3. Operational flow of the suggested model

E. Implementation

The model is implemented using popular deep learn-ing libraries such as TensorFlow or PyTorch. We use relevant libraries and frameworks (eg LIME library) for data processing, model training and XAI analysis. Specific hardware and software configurations are determined based on computer requirements and resource availability.

IV. RESULTS T

A. Training Details

The Adam optimizer, which is a well-liked option for deep learning applications because of its variable learning rate capabilities, was used to carefully train the U-Net model. The model's weights were updated iteratively over five epochs, a reasonable choice considering the complexity
of the task and computational constraints. The choice of the cross-entropy loss function, a standard choice for classification problems, ensured that the model learned to differentiate between liver tissue and tumor lesions effectively. Training was conducted on a high-performance computing cluster, harnessing the parallel processing power of a single NVIDIA Tesla V100 GPU, which expedited the training process significantly.

B. Training Performance

Throughout training, the U-Net model showed apprecia-ble gains in both training and validation losses. The val- idation accuracy consistently increased, reaching 99.52% after 5 epochs. The U-Net model demon- strates remarkable performance and effectiveness in seg- menting liver tumors. Notably,The validation loss dropped from 3.0009 in the first epoch to -0.0046 in the last, demonstrating the model's excellent performance and good convergence.These results suggest that the U- Net model is capable of accurately identifying liver tumors in medical images, which is crucial for diagnostic and treatment planning purposes.

TABLE I: MODEL PERFORMANCE

Epo.	Loss	Accuracy	Val.Loss	Val.Accuracy
1	0.2833	96.49%	3.0009	47.77%
2	0.0577	98.95%	0.1177	97.13%
3	0.0193	99.30%	0.0114	99.24%
4	0.0094	99.41%	0.0101	99.25%
5	0.0017	99.56%	-0.0046	99.52%

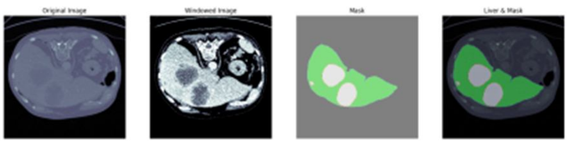

Fig. 4. Liver and Tumor Segmentation

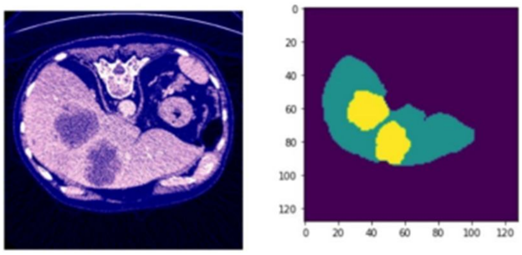

Fig. 5. Input image and Tumor highlighted

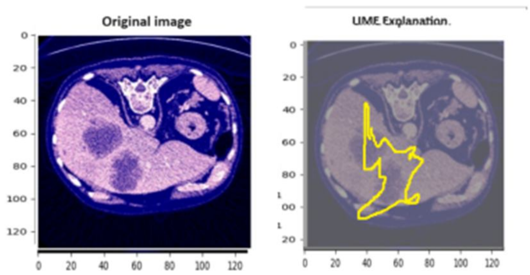

Fig. 6. Lime-enhanced tumor visualization [Tumor 1]

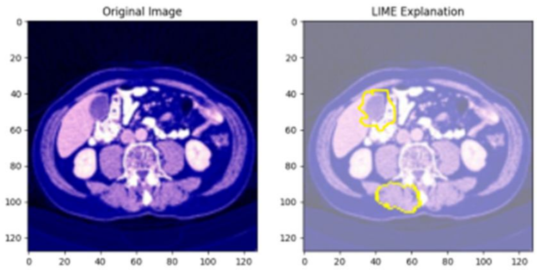

Fig. 7. Lime-enhanced tumor visualization [Tumor 2]

The training process yielded promising results, with the above metrics (Table.1) recorded during the training phase.

C. Model Evaluation

Standard measures for image segmentation tasks, such as precision, accuracy, recall, F1 score, and dice factor, are used to assess our model's performance. We evaluate our model's performance on a chosen dataset against that of other cutting-edge techniques. We aim to demonstrate that our model achieves high accuracy while providing valuable information about its decision-making process, increasing confidence and understanding of its clinical application.

D. Implementation of LIME

After implementing the Lime feature into our framework, we observed a significant enhancement in the interpretabil-ity of our U-Net model's predictions. Lime effectively highlighted the regions of the tumor within the liver, pro-viding clear and intuitive explanations for why the model made specific predictions. By perturbing the input images and analyzing the changes in predictions, Lime accurately identified the area of image that influenced the model's decision-making process.

The above segmentation output unequivocally demon-strates the efficacy of our model in accurately delineating liver tumors from surrounding hepatic tissue. In the visual representation, the liver region is depicted in a distinct green hue, while the white delineations precisely highlight the tumor regions.

This clear differentiation underscores the robustness of our trained model, affirming its capacity to discern between healthy and malignant tissue with high fidelity.

In the following results(figure.5), the input image of a test file is visualized alongside the corresponding predicted mask generated by the model. This visualization aids in as-sessing the model's performance, particularly in accurately segmenting liver tumors from the surrounding tissue

We were able to better understand the behavior of the model by gaining insightful knowledge about the attributes that underlie its predictions thanks to this degree of de-tail.Moreover, the Lime-generated explanations facilitated clinicians in comprehending and trusting the model's out-puts more effectively. By visually demonstrating the regions of interest within the liver, Lime empowered clinicians to make informed decisions in medical diagnoses, ultimately contributing to the advancement of liver cancer detection.

Overall, the integration of Lime into our framework proved to be instrumental in improving the transparency and in-terpretability of our U-Net model, thereby enhancing its utility in clinical settings.The figure.6,7 is the examples of Highlighted tumor regions within the liver, generated by Lime, providing interpretive insights into the U-Net model's predictive reasoning.

V. CONCLUSION

In conclusion, our research presents a pioneering ap-proach to addressing the critical challenge of liver cancer detection through the synergistic integration of deep learn-ing and explainable AI techniques. Leveraging the power of U-Net, a robust deep learning architecture, in conjunction with LIME, a leading explainability method, our proposed model offers not only enhanced accuracy in tumor detection but also invaluable insights into decision-making process of the AI system. By elucidating the rationale behind each prediction, our framework fosters transparency and trust, essential for the acceptance and adoption of AI in clinical practice. The impressive results obtained through meticulous training and validation underscore the efficacy and reliability of our model in accurately delineating liver tumors from surrounding tissue, thereby facilitating early diagnosis and treatment planning. Furthermore, the suc-cessful implementation of LIME significantly augments the interpretability of our model's predictions, empowering clinicians with actionable insights for informed decision-making.

Overall,Our study is a major contribution to the field of liver cancer detection and has broad ramifications for enhancing patient outcomes and, eventually, lifesaving.

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