



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 12, Issue 9, September 2023

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.423

9940 572 462

6381 907 438

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www.ijirset.com

Liver Cancer Segmentation and Classification

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ABSTRACT: Liver cancer is an illness that could be fatal and also one of the world's fastest-growing cancers types. Lower death rates result through the early identification of tumors in the liver. By examining photos of tissue obtained from a biopsy of this tumor, the goal of this research is to build a model that can assist clinicians in identifying the type of tumor when it develops in the liver's area. To evaluate whether the tumor is malignant and requires therapy, a tissue expert must put up the effort, take the necessary time, and gather the necessary experience. Therefore, a histology specialist can utilise this model to establish a preliminary diagnosis. Convolutional neural networks (CNNs), which can transmit knowledge, will be used in this study to suggest a deep learning model.

KEYWORDS: Liver Cancer, Convolutional Neural Network (CNN), Deep Learning, Medical Imaging, Image Segmentation, Diagnosis, Healthcare Automation, Machine Learning, Cancer Classification.

I. INTRODUCTION

The need of an immediate and precise diagnosis can't be emphasised in the healthcare field where liver cancer cases are rising. Identification of liver abnormalities has benefited by the utilisation of diagnostic imaging procedures like computed tomography (CT) scans. However, this process often demands substantial human effort and expertise. Our project's goal is to utilise the potential of deep learning, more especially CNN, to handle this difficulty, in automating the intricate tasks of segmenting and classifying liver tumors within CT scan images. The potential ramifications of this endeavor extend to enhanced patient outcomes, optimized treatment strategies, and the overall efficiency of healthcare workflows. The primary objective of this effort is to create a sophisticated deep learning system leveraging convolutional neural networks (also known as CNNs) that will automate the difficult process of segmenting and categorising liver cancer utilising computed tomography (CT) pictures. By leveraging the power of CNNs and transfer learning from pre-trained global models, our aim is to enhance the accuracy and efficiency of diagnosing liver tumors, thereby contributing to timely and precise medical interventions. Through the development of this automated solution, we seek to alleviate the burden on healthcare professionals, enabling them to focus on critical decision-making while improving patient outcomes and streamlining healthcare workflows in the context of liver cancer diagnosis.

II. PROBLEM STATEMENT

The core challenge at hand revolves around the laborious and time-intensive process of manually segmenting and classifying liver tumors within CT scans. Healthcare professionals face significant difficulties in meticulously identifying tumor regions and categorizing them based on type or stage. Our project seeks to tackle this challenge by developing an automated. solution that possesses the capability to precisely delineate liver tumors from CT scan images and subsequently categorize them into distinct types or stages. The intricate nature of this problem is accentuated by the complexities tied to distinguishing tumor areas from healthy tissue, stemming from variations in attributes like size, shape, texture, and location.

III. RELATED WORK

[1] This paper evaluates machine learning techniques for liver tumor categorization, emphasizing the importance of medical imaging in tumor identification, diagnosis, and treatment planning. Challenges in liver tumor segmentation, arising from poor contrast and indistinct boundaries, are addressed using multiphase contrast-enhanced CT imaging. Various algorithms, including Support Vector Machine (SVM), k-nearest-neighbor (KNN), decision tree (DT), ensemble methods, and naive Bayes (NB), are applied for classification. Using a dataset comprising 68 CT images with 86 features, the study shows that SVM outperforms other methods, achieving 85% accuracy. DT and ensemble methods exhibit lower accuracy, suggesting SVM's potential as a promising algorithm for liver tumor categorization.

[2] This paper presents a computer-aided algorithm employing SVM for timely liver cancer detection through MRI scans. The algorithm utilizes a histogram-centric approach to extract relevant data from MRIs. It's trained on a dataset of 100 confirmed liver cancer cases, achieving an impressive 86.67% accuracy in early-stage cancer categorization. The study underscores the importance of early liver cancer detection and MRI's potential as a robust diagnostic tool. The fusion of machine learning and MRI scans has proven successful in classifying various conditions. The authors plan to enhance their system by exploring advanced features from texture analysis and sophisticated classification methods, aiming to improve accuracy and effectiveness.

[3] This article conducts a comprehensive literature survey on early liver tumor detection methods, highlighting segmentation challenges like unclear boundaries and appearance variations. The paper discusses various techniques, including morphological reconstruction, watershed transform, NS, FCM, FCN, and FGSA for liver extraction, lesion detection, and tumor region segmentation. Deep learning, particularly CNN, is explored for segmenting colorectal liver metastases (CLMs), yielding notable efficiency improvements. These methods demonstrate high precision in liver tumor classification and segmentation. The study offers a thorough evaluation of diverse methodologies, emphasizing their strengths and limitations in liver tumor categorization and partitioning.

[4] This article proposes an innovative deep learning approach to address liver tumor segmentation and classification challenges using CT scans. It introduces ResUNet and 2D-UNet architectural frameworks, emphasizing their well-structured encode-decoder layer hierarchy. The urgency of precise automated analysis for early-stage liver cancer detection is highlighted due to its significant impact on cancer-related deaths. The paper discusses the complexities of liver tumor segmentation and the potential of convolutional neural networks (CNNs) for this task. Preprocessing steps, including Hounsfield windowing, image normalization, and dataset augmentation, are detailed. The U-Net architecture's effectiveness in biomedical image datasets, especially liver and tumor segmentation, is noted, while acknowledging limitations of traditional model-based approaches.

[5] This research focuses on improving disease prediction by combining genetic algorithms and machine learning, utilizing structured and unstructured data for enhanced accuracy. The study introduces a novel diabetes prediction model, leveraging Naive Bayes and KNN algorithms to augment data. Various machine learning algorithms, including SVM, random forests, logistic regression, and decision trees, are explored for disease prediction, along with feature extraction and dataset partitioning techniques for optimizing results.

IV. PROPOSED SYSTEM

Our proposed system employs advanced deep learning for automated Liver Cancer prediction, utilizing CNN architecture for image classification. It aims to aid in the timely detection of pediatric Liver Cancer, with a primary focus on using CT images. Initial results show promise, outperforming Liver Cancer-Net on CT scans, despite the limited dataset size. Further validation will involve larger datasets and clinical trials.

Advantages of proposed system

- Automation: It eliminates the need for manual segmentation, reducing the time and effort required for diagnosis.
- Accuracy: Leveraging deep learning, our model can achieve higher accuracy and consistency in tumor segmentation and classification.
- Knowledge Transfer: Utilizing existing global models facilitates insights from extensive image datasets, enhancing the model's ability to detect nuanced features.
- Real-time Results: Automated segmentation and classification enable real-time diagnosis, supporting prompt medical decision-making.
- Scalability: Our model efficiently handles large data volumes, suitable for clinical settings.
- Objective Results: Our model reduces inter-observer variability, ensuring objective and reproducible outcomes.
- Potential for Early Detection: Accurate and timely liver tumor detection can lead to earlier interventions and improved patient outcomes.

V. METHODOLOGY

Our approach begins by acquiring a dataset from kaggle.com, a trusted source with diverse datasets suitable for data analysis projects. We specifically select a dataset containing instances of liver disease categorized into two classes. Next, we undergo a crucial data preprocessing phase to enhance dataset quality for effective model training. Various image preprocessing techniques are applied, including image resizing to ensure consistent data point sizes, a

fundamental requirement for training neural networks effectively. The dataset is further divided into two subsets: one for training and another for testing the model's performance, facilitating effective model evaluation on unseen data. The core of our methodology involves data modeling using a Convolutional Neural Network (CNN), well-suited for image-related tasks due to its spatial pattern recognition capability. During training, the CNN learns to differentiate between the two liver disease classes by adjusting network parameters to minimize prediction errors. Following training, model effectiveness is assessed using the testing subset. It involves feeding testing images through the trained model and comparing predicted outcomes to actual labels, generating accuracy metrics such as precision, recall, and F1-score to evaluate model performance. Upon achieving satisfactory accuracy during model evaluation, the final step involves building and saving the model as a file. This file encapsulates the network architecture, learned parameters, and discovered patterns during training. It becomes a ready-to-use tool for identifying and classifying liver disease based on medical images, serving as a foundation for future predictions and analysis in real-world scenarios.

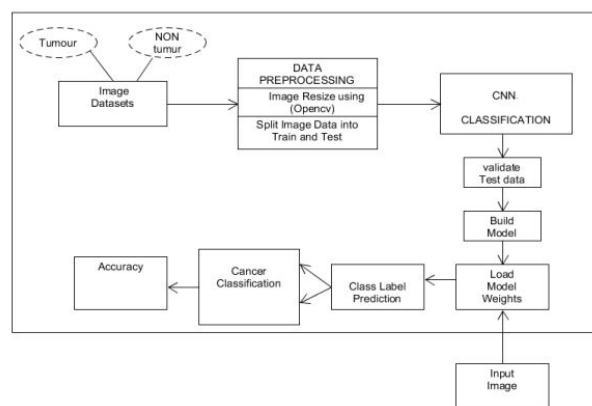


Fig 1: Flow of the project

CNN Implementation:

The process involves loading a pre-trained neural network model for liver cancer prediction from medical images. The model is configured for binary classification ('non-cancerous' and 'cancerous'). It's structured as a sequential neural network with data preprocessing, convolution, pooling, flattening, and dense layers, defined with specific configurations and activation functions.

The model is compiled using the Adam optimizer, sparse categorical cross-entropy loss, and accuracy as a metric. Pre-trained weights are loaded from 'liver_cancer.h5'. Test data, loaded from 'test_data_path,' is converted to an array and expanded as a batch.

The loaded model predicts the image's class probabilities using the 'predict' function, computing confidence scores via softmax transformation. The output displays the class with the highest confidence and its corresponding percentage score.

Finally, the code renders 'result.html,' passing relevant data like the image filename, predicted class label, highest confidence score, and a result indicator (res=1) for user display. This process completes image upload, model processing, and presenting prediction results to the user.

VI. EXPERIMENTAL RESULTS

After using the CNN model to segment and classify between Liver Tumors and Non-Tumors, we got the following result:

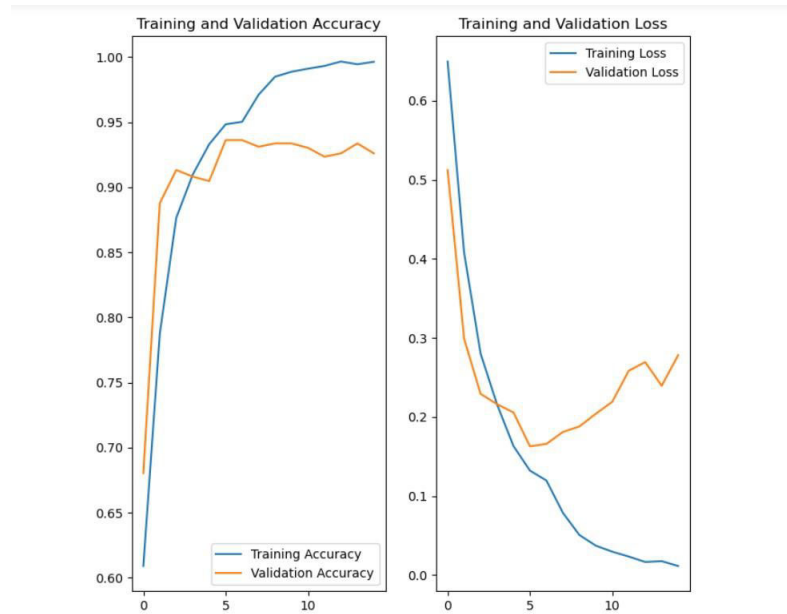


Fig 2: Progress of training the CNN model on our dataset for 15 epochs

Training Progress:

- The training was conducted for a total of 15 epochs (training iterations).
- The loss value steadily decreased from 0.6497 in the first epoch to 0.0114 in the final epoch, indicating a significant improvement in the model's performance over time.
- The training accuracy increased from 0.6090 in the first epoch to a peak of 0.9966 in the 13th epoch before stabilizing.

Validation Performance:

- The validation accuracy reached a peak of 0.9362 during training, suggesting that the model generalized well to unseen data.
- This validation accuracy indicates the model's ability to make accurate predictions on new, previously unseen CT scan images.

Classification Metrics:

- The model's performance was evaluated using classification metrics on a test dataset consisting of 5,874 samples.
- For the "Non Tumour" class, the model achieved a precision of 0.98, recall of 0.97, and an F1-score of 0.98.
- For the "Tumour" class, the model achieved a precision of 0.97, recall of 0.98, and an F1-score of 0.98.
- The overall accuracy on the test dataset was 0.98, indicating that the model correctly classified tumors and non-tumor regions in the liver CT scan images with a high degree of accuracy.

Analysis:

- The training process demonstrated that the model effectively learned to differentiate between tumor and non-tumor regions within liver CT scans.
- The high accuracy and precision scores on the test dataset suggest that the model's predictions are reliable and can be used to assist medical professionals in identifying liver abnormalities.
- The model's ability to generalize to new data (as indicated by the validation accuracy) is a crucial factor in its practical utility.

- The achieved F1-scores of 0.98 for both classes demonstrate a balanced trade-off between precision and recall, which is essential in a medical diagnosis context.

VII. CONCLUSION

The experiment successfully extracted features from liver tumors and classified them using CNN and deep learning approaches. The achievement of strong results was made possible by the use of CT scan image datasets for training and testing purposes. The effectiveness of the suggested technique was also examined through a thorough analysis of performance metrics. The combination of 2D feature maps and several slices revealed the potential for improving the precision of medical picture identification. This experiment demonstrates the promise of deep learning while also laying the groundwork for future initiatives to improve the detection of liver illness.

FUTURE ENHANCEMENT:

Incorporating advanced deep learning techniques, including attention mechanisms, capsule networks, and GANs, can enhance the liver cancer classification model's efficacy. Leveraging pre-trained models and larger external datasets through transfer learning or fine-tuning further improves generalization. Integration of multiple imaging modalities, like MRI and ultrasound, and the development of fusion techniques can enhance accuracy. To tackle imbalanced datasets, oversampling, undersampling, or advanced methods like SMOTE and cost-sensitive learning should be employed. Implementing explainability techniques such as gradient-based CAM and seamless integration with clinical systems via standardized interfaces or APIs are essential for practical medical use.

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Impact Factor: 8.423



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