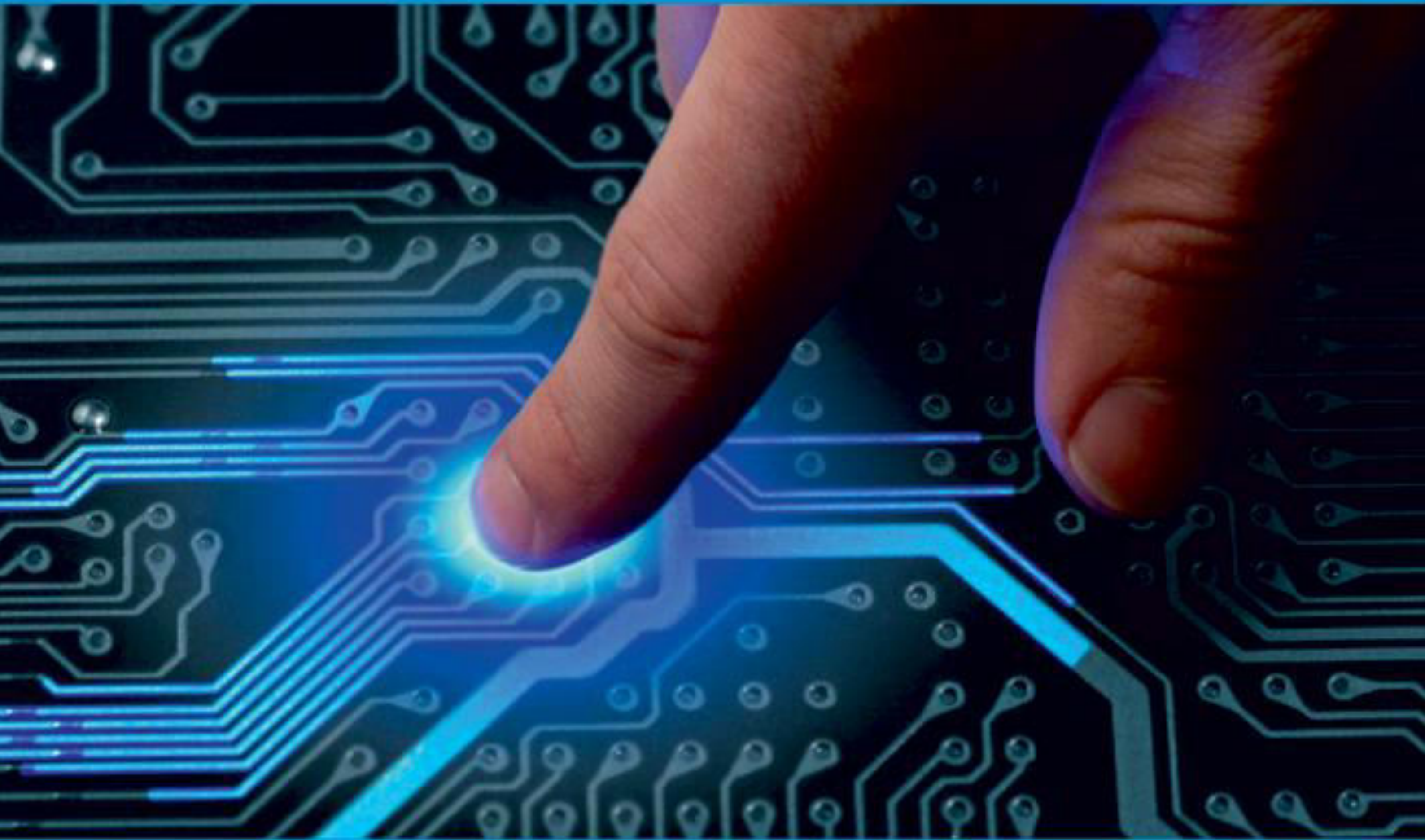
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 12, Issue 11, November 2024

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.625

© 2024 IJIRCCE | Volume 12, Issue 11, November 2024| DOI: 10.15680/IJIRCCE.2024.1211041

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.625| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Advancements in Liver Disease Detection: Hybrid CNN Models for Tumour Identification

Shwetha S[1], Lakshmi M[2], Mohith P Shetty[3], Bhuvana R[4], Likhith H K[5]

Assistant Professor, Department of Computer Science Engineering, Channabasaveshwara Institute of Technology, Gubbi, Tumkur, India[1]

U.G. Student, Department of Computer Science Engineering, Channabasaveshwara Institute of Technology, Gubbi, Tumkur, India[2,3,4,5]

ABSTRACT: Liver diseases, including cirrhosis, non-alcoholic fatty liver disease (NAFLD), chronic hepatitis, and hepatocellular carcinoma (HCC), constitute a serious global health challenge due to their high rates of morbidity and mortality. Precise, timely, and non-invasive diagnostic techniques are crucial for managing these diseases effectively. But conventional diagnostic method like biopsies and imaging scans present limitations, including invasiveness, cost, reliance on specialized expertise, and interpretive variability. Recent Improvement in artificial intelligence(AI), particularly deep learning (DL) methodologies, offer promising alternatives that enhance diagnostic accuracy and automation while remaining accessible. This paper reviews DL-based approaches in liver disease diagnostics, with a focus on the role of CNNs (Convolutional Neural Networks) in medical imaging and machine learning (ML) techniques for handling clinical data interpretation.

In imaging, CNNs have shown significant success in liver segmentation, lesion identification, fibrosis staging, and classification tasks by autonomously extracting complex features from CT and MRI scans. Advanced architectures, such as Hybridized Fully CNNs (HFCNNs), demonstrate better and improved accuracy in liver tumor segmentation, enabling precise assessment of tumor load, planning of treatments, and monitoring clinical response. Enhanced techniques, including attention mechanisms, self-supervised learning, and federated learning, continue to improve segmentation accuracy and diagnosis, underscoring DL's potential to support healthcare professionals effectively. In parallel, ML models analyze non-imaging data like clinical and demographic factors, aiding in risk prediction and disease progression modeling—tools essential for preventive care and individualized treatment plans.

KEYWORDS: Liver tumor, Hepatocellular carcinoma, Convolutional Feature map and Multi-class liver disease classification

I. INTRODUCTION

Hepatocellular carcinoma (HCC) ranks as a major cause of cancer-related fatalities worldwide, with incidence rates escalating in various regions. Early detection is fundamental for improving patient outcomes; however, traditional diagnostic procedures, like biopsies and imaging-based interpretations, present several challenges. For instance, while CT scans play a crucial role in visualizing liver lesions—particularly when combined with contrast agents during the portal phase to enhance lesion visibility—the manual understanding of these scans can be labor-intensive, subjective, and error-prone, especially when dealing with vast and different lesions.

To address these limitations, there is a critical need for automated systems that support clinicians in accurately diagnosing and evaluating liver lesions. Although advancements in imaging technology have improved detection, the automatic segmentation of liver lesions remains complex due to variations in lesion contrast, perfusion levels, and image resolution across patient cases. Conventional machine learning methods, which depend on manually engineered radiological features, struggle to adapt to the nuanced patterns present in medical imaging data.

In this context, deep learning approaches, especially Fully Convolutional Neural Networks (FCNN), have emerged as robust tools for medical image analysis. Distinct from traditional machine learning, FCNNs automatically identify relevant features within medical images, streamlining segmentation processes and enhancing diagnostic consistency,

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which reduces radiologists' workload. This paper proposes a novel Hybrid Full Convolutional Neural Network (HF-CNN) framework for detecting and segmenting liver tumors. Unlike traditional patch-based techniques, the HF-CNN processes whole images, increasing detection accuracy and resolution while employing multi-scale integration to optimize lesion identification and heat map generation. Experimental results confirm the HFCNN model's superior performance in liver tumor segmentation, highlighting its clinical applicability.

II. LITERATURE SURVEY

hepatocellular carcinoma (HCC) one of the liver cancer is a significant health problem, with high mortality rates that underscore the need for early and accurate diagnosis. Traditional diagnostic approaches—like imaging (CT, MRI, ultrasound) and biopsies—rely on skilled clinicians and radiologists. These methods are not only time-intensive but also prone to subjectivity, potentially resulting in diagnostic inconsistencies. The past 10 years we have seen progress in molecular biology, genomics, and imaging technologies, leading to enhanced accuracy in cancer diagnostics. This also includes predictive modeling, which uses individual risk factors to support early interventions and mitigate recurrence risks.

In recent studies, deep learning, particularly CNNs, has shown considerable promise in liver cancer detection and segmentation. For instance, Bai et al. proposed a Multi-scale Candidate Generation (MCG) framework integrating 3D U-Net with Fractal Residual Networks (FRN), enabling improved tumor specificity in CT-based liver cancer detection. Another approach by Das et al. employed a hybrid model that combines Watershed Transform and Gaussian Mixture Models (WT-GMM), achieving a deep learning-driven classification with high accuracy.

The integration of genomic data with imaging data has further elevated the precision of liver cancer detection. The Gene expression profiles provide rich data for differentating cancer subtypes, helping refine predictive models. Researchers like Chaudhury have utilized feature selection techniques to improve model efficiency in identifying critical genes, enhancing diagnostic accuracy. Similarly, the multi-branch CNN approach used in skin cancer detection demonstrates the transferability of CNN frameworks across cancer types, emphasizing the importance of extensive datasets for optimizing model performance. Nonetheless, the success of such deep learning models is heavily influenced by data quality and volume, underscoring the necessity for comprehensive datasets and thorough feature extraction processes.

In conclusion, the convergence of CNNs with other machine learning models and molecular data is transforming liver cancer diagnostics, making early detection more accurate and reliable. Although data quality and model interpretability remain challenges, the potential for hybrid models to revolutionize diagnostics across cancer types is immense.

III. METHODOLOGY

Advancements in liver disease analysis have been largely driven by computational methods, notably deep learning and traditional machine learning, which provide automated, precise, and repeatable diagnostic tools for clinicians. Here, we discuss the core methodologies: deep learning for medical imaging and traditional machine learning for analyzing clinical data.

3.1 Medical Image Analysis using Deep Learning

Deep learning, particularly CNNs, has significantly transformed medical imaging analysis, especially for tasks like segmentation, classification, and anomaly detection. In liver disease applications, CNNs facilitate the identification of liver anomalies with high precision by autonomously learning complex patterns such as shape, texture, and boundaries, which may be challenging to discern through human analysis.

Liver Tumor Detection and Segmentation: CNNs enable highly accurate liver tumor segmentation from MRI and CT images, capturing subtle lesion characteristics often missed in manual analysis. By focusing on features like tissue texture and lesion irregularities, these networks detect early-stage liver tumors, potentially improving patient outcomes through timely intervention.

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End-to-End Learning and Transfer Learning: CNN-based models have the advantage of end-to-end learning, eliminates the need for normal feature extraction. Transfer learning, which utilizes models pre-trained on large datasets, allows efficient adaptation to liver-specific data with minimal labeled samples, reducing data requirements and training time.

Challenges in Application: Despite their effectiveness, CNNs face obstacles in liver disease diagnostics, as the “black box” nature of models of deep learning, which brings interpretability challenging. Variability in imaging protocols also complicates generalization across datasets, a challenge that federated learning aims to address.

3.2 Traditional Machine Learning for Clinical Data Analysis
Traditional ML techniques excel at processing structured clinical data, such as lab tests, patient demographics, and medical histories, contributing valuable insights into liver disease progression.

Support Vector Machines (SVMs) and Random Forests (RF): SVMs are widely used for classifying liver disease stages, while RF models provide robust predictions for conditions like liver fibrosis. These techniques are effective with smaller datasets, unlike deep learning which usually requires large volumes of data.

Logistic Regression and Decision Trees: Both methods have demonstrated utility in predicting disease progression, with decision trees offering intuitive visual representations that aid clinicians in understanding model logic.

IV. RESULTS

In this study, the performance of the Hybrid Full Convolutional Neural Network (HF-CNN) was examined using liver imaging datasets that included CT and MRI scans, sourced from publicly available repositories like the Liver Tumor Segmentation (LiTS) dataset. The model’s effectiveness in identifying and segmenting liver tumors was assessed using indicators such as the Overlap Coefficient (OC), and Mean Error Rate (MER).

Accuracy in Segmentation: The HF-CNN achieved a Dice score above 0.85, indicating strong precision in identifying tumor edges, even under challenging conditions like low contrast or small tumor sizes. The average Overlap Coefficient of 0.82 demonstrated that the model consistently captured tumor regions effectively, showing robustness in handling various tumor forms.

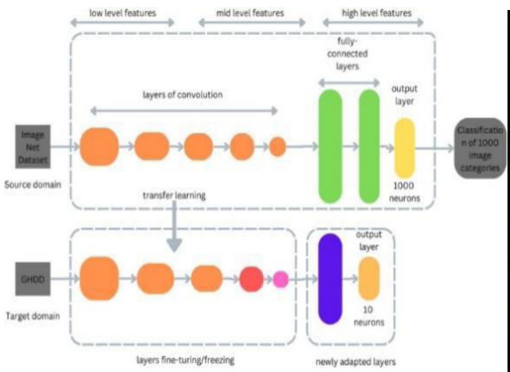

Fig. (a)

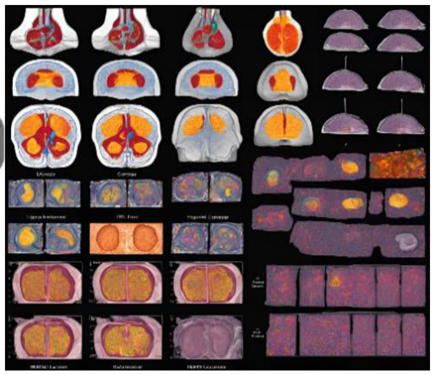
Fig.(b)

Comparison with Conventional Models: When assessed alongside standard models like Support Vector Machines (SVM), Random Forest (RF), and baseline CNNs, HFCNN significantly outperformed these in terms of segmentation. Traditional models performed satisfactorily in classifying images, but they lacked HFCNN’s ability to deliver the fine-grained segmentation necessary for accurately distinguishing liver tumors.

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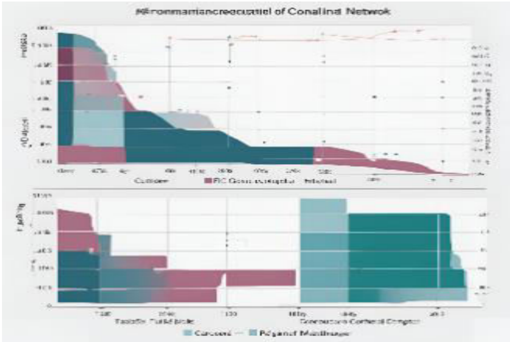

Fig. (c)

Significance of Results: A statistical test (like the t-test) validated the observed performance gains of HFCNN over conventional approaches, suggesting its readiness for clinical use in accurately identifying tumor areas for diagnosis and treatment planning.

Fig. (d)

V. CONCLUSION

This study demonstrates that the Hybrid Full Convolutional Neural Network (HF-CNN) architecture effectively identifies and segments liver tumors with high precision, suggesting its promise as a support tool in liver disease diagnostics. Future research should focus on integrating additional modalities, such as ultrasound data, into the model to further enhance its diagnostic capabilities. Additionally, addressing interpretability concerns by adopting explainable AI techniques could build clinician trust and promote wider adoption of HFCNN in medical settings.

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