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Article

Hybrid contrast-limited adaptive histogram equalization and Deep Learning techniques for improving liver tumor detection

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ABSTRACT

Deep Learning and advanced image processing can enhance the detection and prognosis of liver cancer using medical imaging, such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans. Liver cancer detection is a challenging task due to factors such as poor contrast, noise in imaging techniques, limited annotated datasets, and the complex characteristics of tumors. This study proposes a hybrid technique that combines Contrast-Limited Adaptive Histogram Equalization (CLAHE), Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and Transfer Learning (TL) to improve the precision and accuracy of liver tumor detection. A conventional technique for image enhancement, CLAHE increases the contrast of medical images, making malignant tumors more apparent. CLAHE, however, does not provide a thorough tumor characterization; instead, it focuses on enhancing image quality. CNN is used to extract features, find and learn important patterns, such as edges, textures, and shapes that are pertinent to the diagnosis of tumors. Finally, TL utilizes pre-trained models (Inception V3) for classification, enabling the effective learning of tumor features and achieving high diagnostic precision with fewer computational resources. A hybrid approach combining CNN, GAN, and TL may give an integrated and effective solution for identifying and diagnosing liver tumors. The hybrid technique performed significantly better than independent DL approaches, achieving an accuracy of 93.3%, a sensitivity of 92.2%, a specificity of 94.5%, and an F1-score of 92.8%.

1. Introduction

Liver cancer is one of the main causes of mortality for individuals all over the world. It is challenging and time-consuming to manually identify the cancer tissue in the present scenario. The American Cancer Society predicted that 611,720 people would die from cancer in 2024, while 2,001,140 new cases would be diagnosed. Lung, prostate, and colorectal cancers are the leading causes of mortality for men, and lung, breast, and colorectal cancers are the leading causes for women, accounting for an estimated 611,720 deaths, or about 1671 deaths per day. These findings highlight the persistent difficulties that cancer presents and the need for continual research and advancement in cancer diagnosis and treatment [1]. The cells of the liver are the source of liver cancer, which can either originate in the liver directly (primary liver cancer) or migrate from other regions of the body to the liver (secondary liver cancer). Major risk factors for primary liver cancer include cirrhosis, chronic liver disorders such as hepatitis B or C infection, and heavy use of alcohol. Imaging techniques, including ultrasound, CT, MRI, and PET scans, as well as blood testing for tumor markers such as alpha-fetoprotein (AFP), are necessary for its diagnosis. By detecting liver masses, nodules, or lesions, these imaging methods help patients with liver cancer with diagnosis, staging, and therapy planning [2]. Techniques for image enhancement are essential for raising the visual quality and clinical utility of CT images. Improvements in image enhancement technologies are now crucial for medical practitioners to correctly interpret CT scans, as medical imaging remains an essential component of diagnostic and treatment planning. Tumor segmentation in CT images of the liver can be used to determine the severity of the tumor, schedule therapies, predict outcomes, and monitor clinical response [3]. DL techniques, such as CNN, have shown considerable promise in addressing complex medical imaging challenges, including organ segmentation. CNNs are ideal for medical image analysis because they can automatically detect complicated patterns and discriminate between tissues and organs with high accuracy [4].

Abbreviations

AES	AutoEncoders
CNN	Convolutional Neural Networks
Ct	Computed Tomography
DBN	Deep Belief Networks
FN	False Negatives
FP	False positives
LSTM	Long Short Term Memory
LiTs	Liver Tumour Segmentation
MRI	Magnetic Resonance Imaging
PET	Positron Emission Tomography
RCNN	Recurrent Neural Networks
TCIA	The Cancer Imaging Archive
TP	True Positives
TN	True Negatives

1.1 Medical imaging techniques

Computed Tomography(CT) is a basic imaging method that is widely accessible. A CT scan is a diagnostic technique that uses computer processing to create incredibly precise cross-sectional images, or slices, of the bones, blood vessels, and soft tissues. Compared to standard X-rays, CT scan images offer more information and enable a more accurate assessment of numerous anatomical elements. This imaging approach detects irregularities in soft tissues, circulatory systems, and bones, enabling a more comprehensive examination. It can detect small tumors and provide detailed imaging of liver architecture. CT imaging is utilized to identify tumors, cysts, and masses in the liver, including metastases, cholangiocarcinoma, and hepatocellular carcinoma (HCC). It differentiates between cancerous and benign tumors and assesses tumor vascularity utilizing enhancement trends, such as arterial enhancement for HCC. CT images help in liver cancer staging to assess the location, size, and quantity of tumors and detect blood vessel invasion, such as portal vein thrombosis. Then directs interventional treatments such as transarterial chemoembolization (TACE), radiofrequency ablation (RFA), or surgical excision or transplantation [5]. In liver imaging, CT is a crucial tool, especially when combined with advanced procedures such as triphasic scanning. Depending on clinical needs, CT is often combined with other imaging modalities, such as MRI or ultrasound, to achieve the most effective results.

Magnetic Resonance Imaging (MRI) is an essential tool for detecting liver cancer is magnetic resonance imaging, or MRI. It is generally accepted to be the most sensitive imaging technique for assessing the liver in individuals with chronic liver disease and describing liver cancers. High contrasts between soft tissues in the acquired images are used by MRI, a precise and accurate technique for tumor diagnosis. Although this feature makes MRI especially useful for detecting and describing cancers, circumstances pertaining to the patient as well as the operator may affect the diagnostic efficacy of MRI. Patient-related factors, such as claustrophobia, implanted materials or devices, and unpleasant circumstances, may restrict the use of MRI and affect the caliber of the findings. Because MRI is non-invasive, has excellent imaging capabilities, and can provide both anatomic and physiological information, it is the most commonly used method for diagnosing and characterizing liver cancer. It is particularly important for individuals who are at high risk and who need a precise medical diagnosis and planning.

1.2 Contrast-limited adaptive histogram equalization

A more complex method called histogram equalization modifies an image's dynamic range by changing the pixel values in accordance with the image's intensity histogram. CLAHE is a prevalent image preprocessing technique that enhances contrast by altering image histograms, especially in darker places. It has been demonstrated that CLAHE helps to improve image clarity, especially in medical imaging, where precise tissue segmentation necessitates a high contrast between tissues. While CLAHE enhances contrast, it is unable to fully address other quality issues, including noise, uneven illumination, and border sharpness that are critical for precise kidney segmentation. CNN algorithms must employ sophisticated or relevant preprocessing techniques to improve the quality of images and achieve the best segmentation accuracy [6]. CLAHE is frequently used in medical imaging, particularly for liver image enhancement, to enhance the visibility of features and structures in low-contrast areas. This method is especially useful for enhancing the clarity of liver examination modalities, such as CT, MRI, and ultrasound, where subtle differences in pixel intensity can make it challenging to detect specific abnormalities. It facilitates the differentiation between normal and pathological areas by highlighting subtle variations in tissue architecture, blood vessels, and liver lesions. In technologies such as ultrasound, the contrast-limiting approach lowers noise amplification, which is critical. It is ideal for photographs with poor illumination or shifting contrast, as it focuses on emphasizing specific areas of interest while preserving the entire image [7].

1.3 Deep Learning methods

CNNs have been shown to be highly efficient in medical imaging applications, such as detecting liver cancer. They serve as an important tool for detecting liver cancers such as HCC and its metastases because of their ability to autonomously capture and retrieve structured data from medical images. CNNs can learn complex structures and patterns using unprocessed visual data, eliminating the need for human feature engineering. CNNs are particularly excellent at finding minor anomalies that traditional methods may ignore, as well as distinguishing between malignant and benign liver cancers. It can be used with histopathology slides, CT, MRI, ultrasound, and other imaging modalities. CNNs use a single pipeline to combine preprocessing, feature extraction, classification, and prediction.

A technique for detecting liver cancer is transfer learning, particularly when there is a dearth of labeled medical imaging data. It entails using pre-trained models on big datasets (like Inception V3) and optimizing them on datasets related to liver cancer imaging in order to improve identification, classification, and segmentation tasks. Large annotated datasets are not as necessary with transfer learning, which also speeds up model convergence and enhances performance. TL greatly raises the precision and effectiveness of liver tumor detection tasks by utilizing the advantages of pre-trained models.

The objectives of the study are as follows:

- To improve the identification and categorization of liver cancers in medical imaging by creating a hybrid framework that combines CLAHE for image enhancement and CNN feature extraction
- To apply the pre-trained TL models for the classification of liver cancer diseases to substantially improve the diagnostic accuracy of liver cancer.

The paper's subsequent sections are arranged as follows: Section 2 provides an overview of the current literature related to the present study. A thorough explanation of the techniques utilized to arrive at the best results for the detection and categorization of liver cancer may be found in Section 3. Section 4 presents the outcome and accompanying comments, and Section 5 concludes the study with recommendations for future research.

2. Related works

The incidence of liver cancer has been continuously increasing over time, making it a serious worldwide health problem. For prompt treatment and better patient outcomes, liver cancer must be accurately detected and classified. Sajjanar et al. [8] investigate a variety of strategies, including feature extraction using traditional machine learning (ML) algorithms and segmentation using deep learning (DL) models. The use of ensemble approaches, which aggregate predictions from multiple models to enhance segmentation accuracy, has also been explored. Huang et al. [9] provide a detailed review of a revolutionary image-enhancing procedure that highlights an image's important features by adaptively adjusting the brightness and contrast. Then, to improve the accuracy of tumor region detection, a DL based segmentation network was provided. This network was explicitly trained using the upgraded pictures. Kaur et al. [10] conduct a thorough examination and comparison of numerous image enhancement methods used on medical pictures, with a focus on CT imaging of the abdomen. The study analyzes the benefits and drawbacks of each algorithm by categorizing it into three distinct categories: DL, transformation, and histogram-based methods. The research conducts an in-depth investigation, taking into account factors such as the Structural Similarity Index (SSIM), Mean Squared Error (MSE), Average Mean Brightness Error (AMBE), Entropy, and Peak Signal-to-Noise Ratio (PSNR), to determine how well different techniques perform. Rani et al. [11] suggest a method for classifying and segmenting liver tumors automatically. The three primary parts of our suggested architecture are a pixel-wise classification unit for detecting liver anomalies, a preprocessing unit to improve image contrast, and a Masked Recurrent CNN(RCNN) for liver segmentation. Researchers obtain Dice similarity coefficients of 96% for liver segmentation and 98% for lesion detection with the MICCAI'2027 liver tumor segmentation (LITS) database.

Wu et al. [12] reviewed the latest advancements in DL methods used for liver cancer multimodal fusion image segmentation. The use of DL in multimodal image segmentation for liver cancer is revolutionizing medical imaging and is anticipated to improve the precision and effectiveness. This review offers medical professionals helpful advice and insights. Singh et al. [13] examined DL models for automated liver and tumor area segmentation from CT scans to enhance liver cancer treatment planning and diagnostic precision, utilizing 3200 CT images by choosing around 70% for testing, while the remaining 30% were used for training. Preprocessing techniques include Histogram Equalization and Auto Windowing HU (Hounsfield Units), which help preserve the images' improved clarity. The CNN models, such as ResUNet, VGG16, and VGG19, were employed and assessed using the performance measures, including accuracy, Dice coefficient, IoU (Intersection over Union), precision, and recall. Compared to VGG16 at 93.5% and VGG19 at 91.5%, its hybrid design, ResUNet, which combines U-Net and ResNet, produced improved outcomes with an accuracy of 97.3%. A model's capacity to distinguish between healthy and malignant tissues can be enhanced by extracting pertinent information using the Differential CNN model. The Kernel Extreme Learning Machine (KELM) model is used to classify features into benign and malignant categories. The Differential Biogeography-Based Optimization method (DBBOA) finds near-optimal solutions by fine-tuning the parameters. The DL-based categorization model is trained through this tweaking procedure [14].

Das et al. [15] employed three distinct numerical mapping approaches to digitize the gene sequences. After digitalization, these sequences of DNA were first analyzed in two ways: as 2D spectrogram images and as 1D signals. First, the CNN model was used to analyze the digital sequences as a one-dimensional signal. Second, two distinct 2D CNN models were used to analyze DNA signals after they were transformed into 2D spectrogram pictures. VGG16 produced the feature vectors for the first model, and SVM categorized them. The second model did fine-tuning and added new layers to the VGG16 final output layers. Hameed et al. [16] used CT images from the Kaggle dataset to develop a profound model for identifying liver malignant areas. CT scans from the dataset obtained from the Kaggle platform undergo basic preprocessing. An accuracy value of 94.3% was attained in tumor detection when the suggested model's performance was assessed using various performance criteria.

Gedeon et al. [17] utilized LivlesioNet, which is based on DenseNet, to extract features from the input. At each step, the model produces useful feature maps. The improved multi-scale convolutional layer and LivlesioNet's efforts have reduced the number of parameters, making training with a minimal dataset possible. A bridge scale (BS) is then suggested to combine multi-scale spatial characteristics with the goal of eliminating duplicate features and modifying feature map weights in order to increase accuracy. Furthermore, a fully-connected layer and a SoftMax classifier are coupled for additional classification following the concatenation layer. Bhaskar et al. [18] proposed a method that correctly classifies liver histopathology images as either malignant or non-cancerous, supporting the early identification of the emergence of liver cancer cells that may invade or disseminate. Although histopathological image analysis (HIA) is crucial for identifying the growth of cancer cells, it is laborious, prone to errors, and reliant on the skill of the pathologist. In order to increase precision as well as effectiveness in liver cancer cell proliferation, this research suggests an automatic HIA that makes use of DL. The model employs multiple instances learning for picture-level classification, ResNet50 for patch-level feature extraction, OpenCV libraries for image preprocessing, and whole slide image (WSI) input. Ma et al. [19] constructed a Transformer structure block with a dense residual attention CenterNet network to suggest a liver tumor detection technique called TDCenterNet. A dense residual attention network is intended to improve feature flow in cases where lesion features are not sufficiently extracted. The dependencies between global characteristics are captured by embedding transformer structural blocks. To retrieve lesion characteristics of varying sizes, atrous spatial pyramid pooling is incorporated. A knowledge distillation training approach is created to enhance TDCenterNet's performance. According to earlier research investigations, the most difficult jobs are those involving computationally complex, sensitive parameter setups, misdetection, and misclassification.

3. Methodology

The proposed approach combines CLAHE for image enhancement, CNN for feature extraction, and transfer learning for classification, as shown in Figure 1. The suggested hybrid method's deep learning component includes: CLAHE, CNN, Data Augmentation, and Transfer Learning models. The detailed flow diagram is shown in Figure 2.

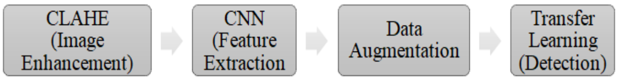

Figure 1. Proposed method

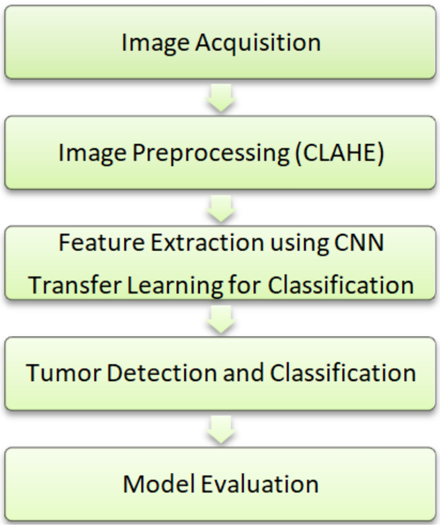

Figure 2. Detailed Workflow –Proposed Method

3.1 CLAHE

A histogram equalization method called CLAHE prevents noise amplification and over-enhancement by minimizing amplification in homogenous areas, thereby improving image contrast. The suggested approach applies CLAHE to liver imaging pre-processing data, highlighting tumor areas and enhancing fine detail visibility. The image has been split into tiles or blocks of a predetermined size (e.g., 8x8 pixels) that do not overlap. Each tile undergoes histogram equalization to improve contrast by redistributing pixel intensity levels. A clip limit, often known as a contrast limit, is used to avoid over-enhancing noise and artifacts. To preserve a smooth contrast, additional histogram counts are uniformly allocated. Then the borders of neighboring tiles are blended using bilinear interpolation, ensuring seamless transitions across the entire image. The input images are optimized for further DL analysis because of this preprocessing phase. The DL model uses the CLAHE-enhanced images as inputs. Robust tumor detection is achieved by the hybrid approach, which combines the advantages of both conventional and AI-driven approaches through improved contrast and sophisticated feature extraction. Figure 3 shows the images of liver tumors before and after CLAHE application. Tumor borders are more obvious on the right side, which shows the heightened contrast produced by CLAHE, whereas the left side shows the original picture with low contrast.

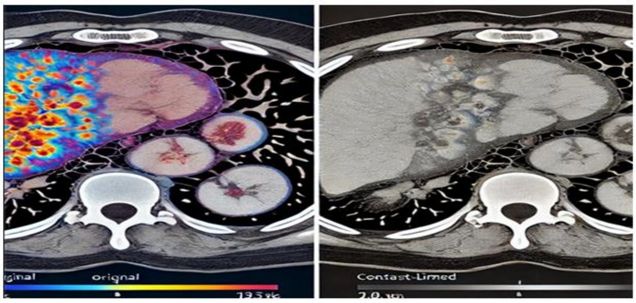

Figure 3. Sample liver tumour image after and before CLAHE

3.2 Convolutional neural networks (CNNs)

The basic components for image categorization problems nowadays are CNNs. However, extracting pertinent information from a picture is another extremely valuable task that is carried out before classification is performed. CNNs use feature extraction to identify important patterns in an image so they can categorize it. The workflow for extracting features from images using CNN is shown in Figure 4. The Conv2d layer is the primary component of a CNN. It extracts key characteristics and reveals hidden patterns. These characteristics serve as building blocks that enable the network to comprehend the content of the image. The Conv2d layer analyzes the picture using filters, also known as kernels. These filters examine tiny regions of the image at a time as they move across it. It converts the raw pixels into useful visualizations and retrieves pertinent information as it goes. This method can identify edges, forms, and their significant aspects in the image. To extract features, a specific CNN architecture is created. The learnt characteristics are captured in feature maps created by the Conv2D layer. The resulting feature maps are sent to the next layers (such as dense and pooling) for additional processing. A variety of liver imaging datasets with tumor areas identified are used to train the algorithm [20,21].

3.3 Data augmentation

Data augmentation is the process of applying several alterations to the current data in order to artificially extend it. Current data points are changed into additional instances of data with the same semantic labels. GANs and AutoEncoders (AEs) are used in this study to generate the images. GAN uses two neural networks: the discriminator and the generator. While the discriminator's role is to distinguish between generated and actual data, the generator's goal is to create data that is indistinguishable from actual data. This configuration allows you to produce highly realistic data samples. AEs, on the other hand, receive a reduced version of the data in a smaller-dimensional latent space and then utilize it to recreate the original data. It is feasible to change the compressed form to generate fresh data points. These strategies enable the deliberate and nuanced creation of data, which has significant benefits in terms of increasing both the variety and accuracy of training datasets [22,23].

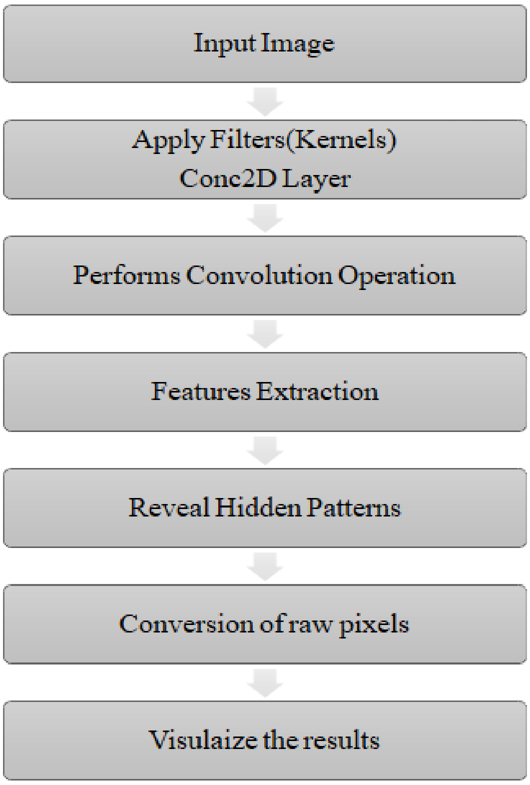

Figure 4. Feature Extraction using CNN

3.4 Inception V3

InceptionV3 is a popular deep CNN for image categorization applications, including medical imaging. Its architecture, which was designed for successful feature extraction, is particularly suitable for complex medical data, such as ultrasound, CT, or MRI scans used to predict liver cancer. InceptionV3 extracts and learns meaningful information from images by processing them across many layers. A number of convolutional and pooling layers are applied to the image. These layers extract low-level features from the input liver picture, such as edges, textures, and basic shapes. InceptionV3 is distinguished by its Inception modules, which have been designed to:

- Extracting multi-scale features involves applying many convolutional filters in parallel, each with a different size (e.g., 1x1, 3x3, and 5x5).
- Minimize the cost of computation by reducing the dimensionality of feature maps through the use of 1x1 convolutions.
- Identify both large lesions and tiny cancers by examining the picture at various dimensions.

The size, form, and texture of liver tumors might vary. Tumor identification is improved by the Inception modules' parallel convolutions, which guarantee that features of various scales are recorded. This enables the network to focus on the most significant characteristics, including aberrant texturing or tumor borders. Auxiliary classifiers are incorporated into intermediate layers of InceptionV3 to aid with learning and avoid overfitting. This is especially helpful in cases where the dataset is minimal, such in the diagnosis of liver cancer. InceptionV3 utilizes global average pooling at the network's end, rather than fully connected layers, to mitigate overfitting and enhance the model's capacity for generalization [24].

4. Results and findings

A hybrid approach integrating CLAHE, CNN, GAN, and Inception v3 for liver tumor classification is implemented in Python using the TCIA dataset.

4.1 Dataset description

The Liver Tumor Collection is maintained by TCIA (The Cancer Imaging Archive). It is a database of imaging results for liver cancer, together with related clinical data. TCIA is a sizable collection of cancer medical images that are openly accessible. According to a common illness picture modality or kind or study emphasis, the imaging data are arranged as "collections." TCIA's main file format for radiological imaging is DICOM. The provision of image-related supporting information, such as patient outcomes, therapy specifics, genomics, and expert evaluations, is prioritized. This dataset includes CT imaging investigations taken before and after TACE in 105 confirmed HCC patients. It contains hand-selected semi-automated segmentations of the liver, tumor, and blood arteries.

4.2 Performance analysis

The hybrid model suggested was assessed through a 5-fold cross-validation and a 70:30 train-test split to assess the robustness and reliability of the performance assessment methods. Final metrics were averaged across the folds during training with cross-validation, to allow consistency with results from the independent test set. Table 1 summarizes the performance comparison. The proposed hybrid approach demonstrated superior performance across all metrics, validating its effectiveness in liver tumor detection. The proposed framework demonstrates notable improvements in classification accuracy, sensitivity, specificity, and resilience across various imaging settings when evaluated on publicly accessible liver imaging datasets [25].

Accuracy: The percentage of cases (both tumor and non-tumor) that were correctly categorized against the total number of cases. It shows the model's overall performance; however, it might not be enough when working with datasets that are unbalanced.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

Specificity: The proportion of real non-tumor instances that were accurately classified as such. It assesses the model's capacity to prevent false alarms, which occur when benign tissues are mistakenly identified as cancers, especially crucial in medical diagnostics to minimize needless procedures.

$$\text{Specificity} = \frac{TN}{TP+FP} \tag{2}$$

Sensitivity: The proportion of real tumor cases that were accurately classified as tumors. It demonstrates the model's accuracy in tumor detection. Early diagnosis and treatment depend on fewer missed instances, which is ensured by high sensitivity.

$$\text{Sensitivity} = \frac{TP}{TP+FN} \tag{3}$$

F1-Score: It balances false positives and false negatives. When datasets are unbalanced and both false positives and false negatives are significant, it can be helpful.

$$\text{F1} - \text{Score} = 2 * \frac{\text{Precision} * \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}} \tag{4}$$

W

where

$$\text{Precsion} = \frac{\text{TP}}{\text{TP+FP}} \tag{5}$$

Comparisons were made between the suggested hybrid approach and standalone DL models with and without CLAHE.

Table 1. DL Methods Vs Metrics(without CLAHE)

Methods Vs Measures	Accuracy (%)	Specificity (%)	Sensitivity (%)	F1-Score (%)
CNN - Inception V3	86.7	84.2	87.6	86.3
RNN	79.5	77.6	81.3	80.4
LSTM	83.1	81.2	85.0	83.5
DBN	80.4	78.8	81.9	81.1

From Table 1, it is clear that all DL models perform lower without CLAHE, most likely because there is less contrast enhancement, making it more difficult to see faint tumor characteristics in the input images. It is evident from Table 2 that CNN performs better than the other models. With an accuracy of 93.9.3%, sensitivity of 92.2%, specificity of 94.5%, and F1-Score of 92.8, the hybrid approach significantly outperformed solo approaches. The integration of CNN, CLAHE, and InceptionV3 contributed to improved detection and reduced false positive rates.

Table 2 DL Methods Vs Metrics(with CLAHE)

Methods Vs Measures	Accuracy (%)	Specificity (%)	Sensitivity (%)	F1-Score (%)
CNN - Inception V3	93.9	92.2	94.7	92.8
RNN	87.5	83.5	87.1	86.3
LSTM	92.7	88.6	91.7	90.9
DBN	90.3	86.2	89.5	88.3

Figure 5 shows the accuracy (%) of several models (CNN -Inception V3, RNN, LSTM, and DBN) in detecting liver tumors with and without the use of CLAHE for image enhancement. After applying CLAHE, all models exhibit a notable increase in accuracy, as seen by the larger red levels relative to the blue levels. When compared to the other models, RNN exhibits the lowest accuracy (79.5%) without CLAHE and a slight improvement (87.5%) with CLAHE. Both DBN and LSTM exhibit notable improvements, with LSTM attaining 92.7% accuracy with CLAHE and DBN reaching 90.3%. Figure 6 shows the specificity (%) of several liver tumor detection models (CNN -Inception V3, RNN, LSTM, and DBN) with and without the use of (CLAHE) for image enhancement is displayed in Figure 6. Applying CLAHE significantly improves the specificity of all models.

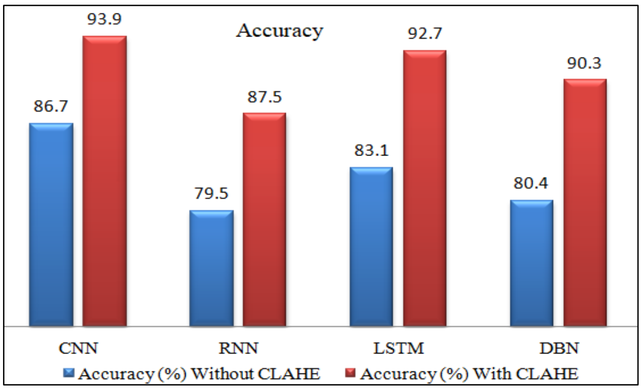

Figure 5. Accuracy- Hybrid and standalone DL methods

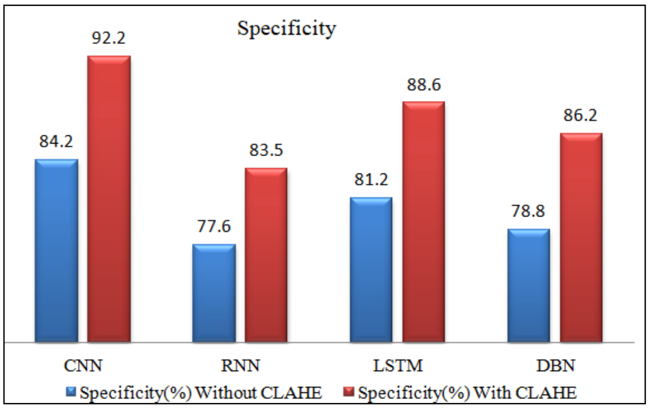

Figure 6. Specificity- Hybrid and standalone DL methods

Because CLAHE increases visual contrast, models can more easily discern between tumor and non-tumor areas. CNN's exceptional ability to extract spatial characteristics and prevent false positives is demonstrated by its maximum specificity with CLAHE (92.2%). Although specificity is lower (84.2%) without CLAHE, it is still superior to most models. RNN has the lowest performance (77.6%) of any model without CLAHE. Although it increases to 83.5% with CLAHE, it is still behind CNN-Inception V3, LSTM, and DBN. With CLAHE, LSTM significantly improves from 81.2% (without CLAHE) to 88.6%. It can handle improved images more efficiently since it can process sequential information. DBN increases to 86.2% (with CLAHE) from 78.8% (without). Despite having a simpler design than CNN, it still gains a lot from CLAHE. Both with and without CLAHE, CNN -Inception V3 has the maximum specificity, proving its advantage in precisely detecting negative situations.

Figure 7 shows the sensitivity of many DL models (CNN -Inception V3, RNN, LSTM, and DBN) with and without the use of CLAHE. CNN has a sensitivity of 94.7% with CLAHE and 87.6% without it. With CLAHE, sensitivity rises noticeably. All of the models' sensitivity is increased by using CLAHE. For CNN -Inception V3, the improvement is very noticeable. This implies that CLAHE preprocessing improves the quality of input data, which in turn helps DL models perform better.

Figure 8 shows the F1-score (in %) of DL models like CNN Inception V3, RNN, LSTM, and DBN, which contrasts them in two scenarios: one without CLAHE and one with CLAHE. CNN demonstrates a notable improvement in F1-score of 86.3% without CLAHE and 92.8% with CLAHE. CNN and LSTM models show the highest gain, indicating that CLAHE improves both models' performance and data quality. This is consistent with CLAHE's objective of enhancing feature clarity for tasks using images or data. This study proposes a novel approach to liver tumor detection using a hybrid framework that integrates task-specific GANs to generate realistic tumor patterns with CLAHE for contrast enhancement of liver tumor images. Transfer Learning uses Inception V3, which is identified as one of the most effective models for medical image classification. Rather than relying on existing isolated techniques, the aforementioned components are integrated into an optimized workflow that respects their interdependencies. The combination of these integrated elements has led to a significant improvement in accuracy, sensitivity, and specificity with regard to correctly identifying liver tumors.

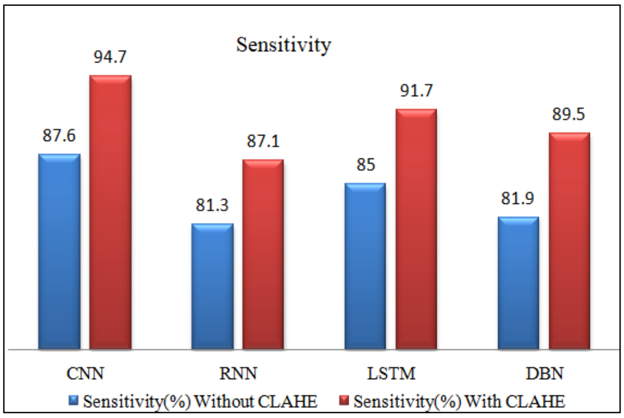

Figure 7. Sensitivity- Hybrid and standalone DL methods

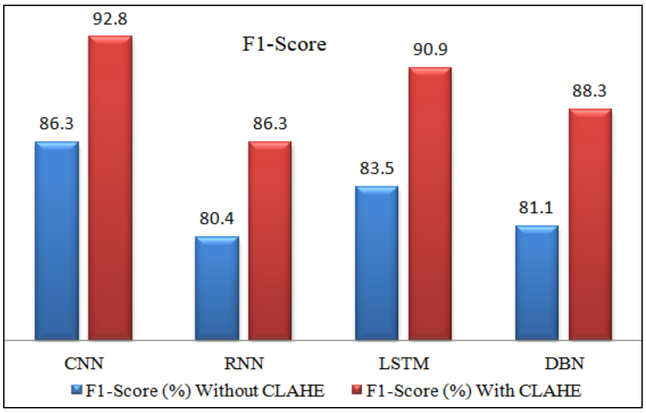

Figure 8. F1-Score- Hybrid and standalone DL methods

Table 3 presents a comparison table that highlights the positive aspects and drawbacks of the suggested approach in contrast to the current methods. This hybrid technique paves the path for more efficient and scalable medical imaging solutions by highlighting the complementary abilities of image enhancement, feature extraction, data augmentation, and transfer learning in addressing the complexity of liver tumor identification. CNN - Inception V3 techniques have revolutionized the detection of liver cancer by providing automated, high-accuracy lesion detection, categorization, and segmentation solutions. CNN - Inception V3 will remain essential in enhancing liver cancer detection and improving patient outcomes as artificial intelligence and computing power continue to advance.

Table 3. Strengths and limitations of the proposed method compared to existing methods

Method	Strengths	Limitations
Proposed Hybrid (CLAHE + GAN + Inception V3)	Improves image contrast with CLAHE, enhancing tumor visibility.- Task-specific GAN generates realistic, tumor-like images.- Inception V3 efficiently handles fine-grained features with transfer learning.- Integrated, cohesive workflow improves accuracy and consistency.	Computationally intensive due to multi-step processing.- Requires careful hyperparameter tuning for GAN and CLAHE settings.- Still dependent on availability of quality annotated baseline images for GAN training.
CNN-based Methods	Learns hierarchical image features directly from data.- Flexible architecture customization.	Requires large annotated datasets.- Prone to overfitting on small datasets.- Poor generalization without data augmentation.
CNN + TL	Utilizes pre-trained models, reducing training time and data requirements.- Improved feature extraction from medical images.	Limited to features learned from non-medical (generic) images.- May not capture fine-grained tumor-specific patterns effectively.
CNN + GAN	Addresses data scarcity by generating synthetic images.- Enhances model robustness with diverse training data.	GANs may produce unrealistic or noisy images without careful tuning.- Often lacks tailored tumor-specific image characteristics.

Overfitting, a common machine learning issue where models trained on sparse data perform well on training data but poorly on unknown data, is what data augmentation attempts to minimize. CLAHE greatly improves contrast and the identification of critical traits in every model, resulting in better outcomes across every metric. CNN-Inception V3 outperforms in all statistics due to its superior spatial feature extraction capabilities. Because of its picture data optimization, CNN routinely outperforms RNN, LSTM, and DBN. Because it can handle long-term dependencies, LSTM beats RNN and might be beneficial for processing sequential image data. Because of its simplistic design and lack of complicated sequential or spatial feature training capabilities, DBN performs just marginally higher than CNN-Inception V3.

A revolutionary method for detecting liver cancer, transfer learning tackles important issues in medical imaging such as data variability and shortage. Better patient care is made possible by using pre-trained models to enable quicker and more accurate diagnosis. The outcomes validated Inception V3 high liver/tumor segmentation precision, which would be helpful for physicians to get adequate diagnostic improvement. Inception V3 architecture, which was created especially for the medical imaging segmentation tasks in this study, shows promise as a flexible framework that might be integrated into automated oncological diagnostic tools and drastically alter the identification of liver cancer.

This hybrid method improves the accuracy and durability of liver tumor detection systems by combining the benefits of contrast enhancement, complex feature extraction, and categorization. While the hybrid technique produced promising results, drawbacks such as higher computational difficulty and reliance on high-quality annotations were discovered. Future study will look at optimization approaches and unsupervised learning to improve scalability and usability to larger datasets.

5. Conclusion

This study presented a hybrid framework that included CLAHE for image enhancement, CNN for feature extraction, and Inception v3 for tumor diagnosis. Integrating classical image processing with cutting-edge AI technologies provides an effective approach to addressing obstacles in medical imaging diagnosis. The results highlight the promise of hybrid approaches for improving detection accuracy and patient outcomes. CLAHE effectively increases contrast in liver images, making tumors more apparent and improving feature extraction. CNNs extract strong features by recording the textural and spatial information required to identify liver cancers. Because of its efficient design and multi-scale feature extraction capabilities, InceptionV3 detects liver cancer with high accuracy, sensitivity, specificity, and F1-score. The hybrid framework outperforms conventional algorithms in terms of overall classification accuracy, F1-score, and sensitivity. This improvement is due to an effective combination of DL techniques and CLAHE. The current work might be expanded to incorporate automatic liver and tumor segmentation, allowing for exact localization and tumor size estimation. More studies and clinical validation are required to turn these developments into real-world applications. Future research could work around these limitations with the inclusion of automatic liver and tumor segmentation modules, allowing for precise tumor localization and size estimation for increased clinical applicability. The dataset may be enlarged by collaborating with multiple centers to regularly add a diverse cohort of cases to their overall model years. Furthermore, a lightweight model architectures or optimization techniques that conserves computational expense and can be adopted in clinical settings, along with the auto-segmentation and the dataset. Generally, the framework will need longitudinal clinical validation and randomized trials to prove that it works and is safe in practice.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The author adheres to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

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