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Automated Liver Disease Classification Via Modified ResNet-50 Architecture on CT Images

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A B S T R A C T

The classification of liver diseases is fundamental for the prompt identification and management of hepatic illnesses. In recent years, many computer-aided diagnostic systems for liver lesions have been developed based on deep learning techniques. This paper describes the design and assessment of the Automated classification of liver diseases with the use of Computed tomography (CT) imaging using a Modified residual convolutional neural network (ResNet-50) model. The dataset comprised many classifications of liver tissues, including cirrhosis, benign tumors, malignant tumors, and normal liver cells. The model performed training, validation, and testing, attaining excellent results with a training accuracy of 99.1%, validation accuracy of 96.4%, and test accuracy of 99.3%. This precision surpasses that of several leading approaches. The findings achieved with the proposed framework illustrate the effective execution of the experiment for practical application in liver tumor screening. By augmenting the accuracy of diagnostics, this research addresses Goal 3: Good Health and Well Being. It also encourages new developments in AI technologies and medical imaging, which shifts the focus to the integration of AI powered systems within health care for achieving Goal 9: Industry, Innovation and Infrastructure and subsequently, the development of medical technology and healthcare globally.

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1. Introduction

Liver cancer, particularly hepatocellular carcinoma (HCC), is one of the most prevalent and lethal malignancies globally[1], contributing significantly to cancer-related morbidity and mortality. Early and accurate detection of liver tumors is crucial for effective treatment strategies, including surgical resection, liver transplantation, or targeted therapy[2]. The clinical management of liver cancer heavily relies on diagnostic imaging techniques such as computed tomography (CT), which provides high-resolution cross-sectional images that allow for the detection[3], characterization, and monitoring of liver lesions[4]. However, the manual analysis of CT images is often subject to human limitations, including diagnostic errors due to the complexity of liver anatomy and tumor heterogeneity[5].

In response to these challenges, the field of medical image analysis has seen a significant transformation with the advent of artificial intelligence (AI) and machine learning (ML) techniques[6], particularly deep learning (DL) algorithms[7]. Among these, Convolutional Neural Networks (CNNs) have emerged as the most effective deep learning models for image classification tasks due to their ability to automatically extract hierarchical features from raw image data. CNNs have shown considerable promise in medical imaging applications, including the classification of liver tumors[8]. One such architecture that has gained widespread attention is ResNet50, a deep residual network known for its ability to train very deep networks by mitigating the vanishing gradient problem[9]. The ResNet50 model's residual learning framework allows it to preserve critical information while enabling efficient training, even with a large number of layers[10].

This study investigates the use of a modified ResNet50 model to classify liver tumors into four categories: benign, malignant, cirrhosis, and normal, using CT images. The standard ResNet50 architecture is modified by fine-tuning various layers, adjusting hyperparameters, and employing advanced optimization techniques to improve performance on liver tumor classification tasks[11]. The goal of these modifications is to enhance the model's sensitivity and specificity in distinguishing between the different tumor types, ultimately leading to more accurate and reliable predictions[12].

The dataset used in this study comprises a diverse set of CT images, representing various stages and types of liver tumors, as well as normal liver tissue. Preprocessing steps such as image normalization, data augmentation, and patch extraction are applied to improve the model's robustness and reduce overfitting. In addition, transfer learning is utilized to leverage pre-trained weights from the original ResNet50 model, which helps accelerate the training process and enhance the model's ability to generalize to unseen data[13].

The model's performance is evaluated using a variety of performance metrics, including precision, recall, specificity, and the F1-score. These metrics are critical for assessing the model's ability to correctly classify each tumor category while minimizing false positives and negatives. Comparisons are made between the modified ResNet50 model and other traditional machine learning models and CNN architectures to assess its relative performance in liver tumor classification[14].

This article aims to demonstrate the potential of deep learning, specifically modified ResNet50, in automating the classification of liver tumors from CT images, offering a powerful tool to assist radiologists and clinicians in diagnosing liver diseases more accurately and efficiently. Furthermore, it discusses the challenges associated with medical image classification, including the need for large annotated datasets, model interpretability, and the limitations of current algorithms[15]. The findings of this study are expected to contribute to the growing body of research in medical image analysis and underscore the importance of leveraging AI for improving healthcare outcomes. This study aids in the advancement of the UN Sustainable Development Goals, particularly with regard to Goal 3: Good Health and Well-Being, as it formulates machine learning systems for diagnosing liver diseases. This aids in achieving early diagnosis, appropriate treatment, faster recovery, lower costs of healthcare, and improved quality of life for the patients[16]. Moreover, it advances Goal 10: Reduced Inequalities by making diagnostic services more accessible to the people, which enhances universal health coverage [17]. It also assists in the fulfillment of Goal 9: Industry, Innovation, and Infrastructure by promoting the use of AI in medicine and creating strong health systems that diminish health inequities and are able to provide quality services to many different people [18].

The paper is divided into sections with specialized purposes. Section 2 is a literature review of the field's background and knowledge. Section 3 explains the experimental setup, including training, testing, and assessment data split, data preprocessing, and augmentation. Section 4 describes the proposed ResNet50 approach, architecture, mathematical representation, model optimization, and training, which includes experiment findings and analysis. Section 5 provides the results of the modified ResNet-50 and discussion. Finally, the Future Directions and conclusion summarize the findings and emphasize the study's importance.

2. Literature Review

The classification of liver tumors using CT and MRI scans has continued to be a focal point of research. Many systems have been put forward by researchers to classify liver lesions in relation to the tissue by feature extraction from the lesion region. Recent developments in the liver pathology classification techniques are discussed below along with the advancements in the artificial intelligence technologies.

In 2017, Christ et al. proposed a method for automating liver and tumor segmentation from CT and MRI volumes using cascaded fully convolutional neural networks (CFCN). Their method first performs liver segmentation and then lesions are found in the liver region. The results are much more accurate. Further improvement was achieved with a dense 3D Conditional Random Field (CRF), which produced over 94% Dice scores in liver segmentation. This demonstrated robustness across diverse imaging modalities and data heterogeneity, and showed practical clinical and large-scale medical research applicability[19].

In 2018, Wang et al. studied the categorization of focal liver lesions with deep learning using a modified ResNet model. The study emphasizes how transfer learning for classification accuracy of 83.7% was improved to 91.2% with a small number of training samples. This approach exceeds the performance of other methods, proving that deep learning techniques can be useful in medical imaging for the diagnosis of liver cancer[20].

In 2019, Chen et al, proposed an adversarial densely connected network (ADCN) to segment liver tumors from CT images. The method tackles difficulties such as noise and variability in tumors through a two-stage cascade approach: first, liver segmentation is performed by an MPNet multi-plane integrated network (MPNet), and then tumor segmentation is executed by ADCN. The average Dice score obtained was 68.4%, along with improved results in other metrics after the implementation of adversarial training and dense connections, signifying enhanced accuracy in segmentation [21].

In 2020, Srivastava et al. designed a model for early detection and classification of liver cancer by integrating CT and MRI images. Their model uses Discrete Wavelet Transform (DWT) for image fusion, Speeding up robust features (SURF) for feature extraction, Cuckoo Search for feature selection, and Gaussian Naïve Bayes for classification. This approach resulted in 99.9% accuracy and it greatly improved the medical imaging quality and diagnosis accuracy, which is helpful in clinical decision-making and automated tumor diagnosis[22].

In 2021, Xia et al, developed a 3D fully convolutional neural network employing a variant of squeeze-excitation (SE) technique for precise liver segmentation in abdominal CT scan images. The model, which combines spatial and channel recalibration blocks, is referred to as the 3D Modified Space and Channel Recalibration (MSCR) U-Net model. Their model was evaluated on the LiTS and 3DIRCADb datasets, surpassing previously existing techniques like Attention U-Net and ResU-Net by performing exceptionally well with an average Dice score of 94.8%. It also showed significant improvements in segmentation precision, accuracy, and stability, overcoming the difficulties posed by the diverse shapes of the liver and intricacies of surrounding tissues[23].

In 2022, Ragab et al. introduced an Intelligent Artificial Intelligence with Equilibrium Optimizer Based Liver Cancer Classification (IAIEO-LCC) model, which uses CT scans for liver cancer diagnosis. The model employs median filtering for image processing, utilizes Kapur's entropy for segmentation, extracts features using Visual Geometry Group (VGG-19), and identifies them with a Stacked Gated Recurrent Unit (SGRU) classifier. The accuracy of the IAIEO-LCC technique for the detection of liver cancer was demonstrated by its 98.52% accuracy, which outperformed other models in terms of sensitivity, specificity, and total classification[24].

In 2023, Balasubramanian et al, explains how Enhanced Swin Transformer Network with Adversarial Propagation (APESTNet) utilizes Mask R-CNN for liver tumor segmentation and classification. It addresses the problem of accurately detecting liver tumors based on their diverse shapes and faint boundaries. The described approach involves a three-stage framework, consisting of pre-processing, segmentation, and classification, which was improved with histogram equalization and median filtering. Results suggest that APESTNet works best, midrange over-segmentation problem not with standing, but does have some minor issues of over-segmentation. the proposed model accuracy of 95.62%, F-1 measure of 94.53%, precision of 98.32%, and recall of 94.62%, respectively[25].

In 2024, Stephe et al. proposed a Vision Transformer-Gated Recurrent Unit (ViT-GRU) for classification and a Transformer based Attention Guided Network (TAGN) for liver tumor segmentation from CT scans. To boost segmentation performance, TAGN incorporates multi-scale skip connections along with self-aware attention. The extracted features are efficiently classified by the ViT-GRU model. Experimental results showed TAGN achieving a mean accuracy of 84.65%, while ViT-GRU achieved a recall of 95.21% and an accuracy of 97.57%. The methods proposed greatly enhance the accuracy of liver tumor diagnosis[26].

In 2024, Appati et al. developed a multiattention network by integrating a ResUNet-based cascaded architecture and a U-Net with self-attention for liver tumor segmentation improvement from CT scans. Their approach effectively solved the problems of identifying liver tumors with different diameters, resulting in high Dice coefficients for liver and tumor segmentations at 0.92 and 0.83 respectively[12].

In 2025, Balaji et al. suggested a new technique that integrates Convolutional Neural Networks (CNN) and ResNet in the approach system for the liver tumor detection in CT scan images. The suggested solution improves the liver tumor detection accuracy using CNN for liver segmentation and ResNet for feature extraction. The approach deals with the problems related to medical image analysis, including noise and image variability. Using the dataset of 130 CT images, the system remarkably achieved an accuracy rate of 99.7%[27].

After undergoing analysis of the literature, several researchers attempt to diagnose liver disease using different methods with the aim of improving accuracy. Besides such advantages, problems like the class imbalance, the interference in medical images, and the demand for precision in the AI outputs still exist.

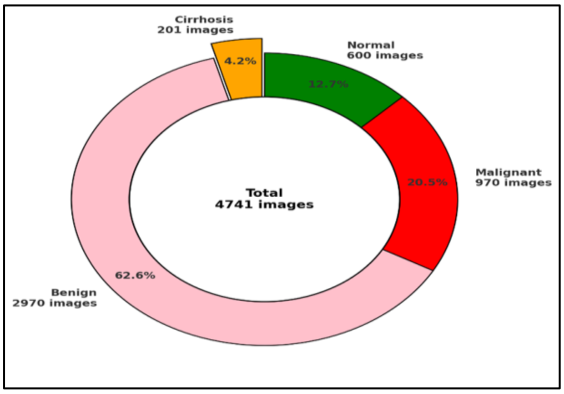

Fig. 1. Dataset distribution among multiple classes (Benign, Malignant, Cirrhosis and Normal) indicated in the dataset used for training and validation.

3. Methodology

3.1. Tools and setup

The research was conducted using a laptop including 16GB of RAM and an Intel(R) Core(TM) i7-10510U CPU operating at 1.80GHz, with a boost frequency of 2.30GHz and dual CPU architecture. The dataset was divided into training, validation, and testing sets at a ratio of 70%, 15%, and 15% respectively. The software framework utilized includes Conda 23.9, Python 3.11.5, and TensorFlow 2.18 packages. Furthermore, the subsequent libraries were utilized: Keras, NumPy, Pandas, Matplotlib, Scikit-learn, Jupyter Notebook, Training was conducted on a single CPU with a learning rate of $1 * e{-}4$, a hyperband search factor of 3, a decay rate of 0.9, a minibatch size of 46, the Adam optimizer, and a piecewise learning rate. The model was trained for 80 epochs, with each epoch including 104 iterations.

3.2.Dataset

The liver tumor dataset acquired via Kaggle[28], which includes CT images, is a significant resource for the study and analysis of liver diseases. Two datasets were amalgamated: one pertaining to liver tumors and the other to liver cirrhosis, divided into four categories (benign, malignant, cirrhosis, and normal). Figure 1 illustrates the data distribution for the Modified ResNet50 model.

A total of 4,741 CT images were utilized for the training, validation, and testing of the developed classification model. The liver disease datasets have been split into three categories: 70% for training, 15% for validation, and 15% for testing.

3.3.Data Preprocessing and Augmentation

A robust and comprehensive data collection and preparation pipeline is essential for the accurate classification of various liver diseases. The data collection has the images necessary to represent each of the four types of liver diseases. The dataset images are cropped to 224 pixels in both height and width, with three color channels (RGB) to comply with the specifications of the ResNet50 model.

The first step is to set the range for the image data to be between zero and one. To accomplish this, the pixel values are divided by 255, thus changing the original set of 8-bit integers (0-255) into a set of float values, { 0, 1 }. The training dataset is augmented in the last step. Our model illustrates the implementation of data augmentations with the ImageDataGenerator class provided in the Keras framework. This class enables the generation of new training samples by modifying existing images via rotation, height and width adjustments, horizontal flipping, and zooming.

3.4. Proposed model

In this work, we present a modified ResNet-50 deep convolutional neural network (CNN) structure that has been specialized for liver disease classification. The same model can also be used for other types of image analysis because it is extremely good at complex pattern recognition in images in addition to its primary function as an image classifier. The workflow of the proposed technique, ranging from data preprocessing to the end output, is illustrated in Figure 2.

1. ResNet architecture

ResNet-50, comprising 50 layers arranged in several convolutional blocks illustrated in Figure 3, is a variant of Residual Networks (ResNets) created by He et al. [29] that incorporates skip connections or residual blocks to address the vanishing gradient problem in deeper architectures. This model is designed to perform a series of convolution operations, with batch normalization and activation functions applied after each operation, which produces a feature map for classifying the image at a later stage.

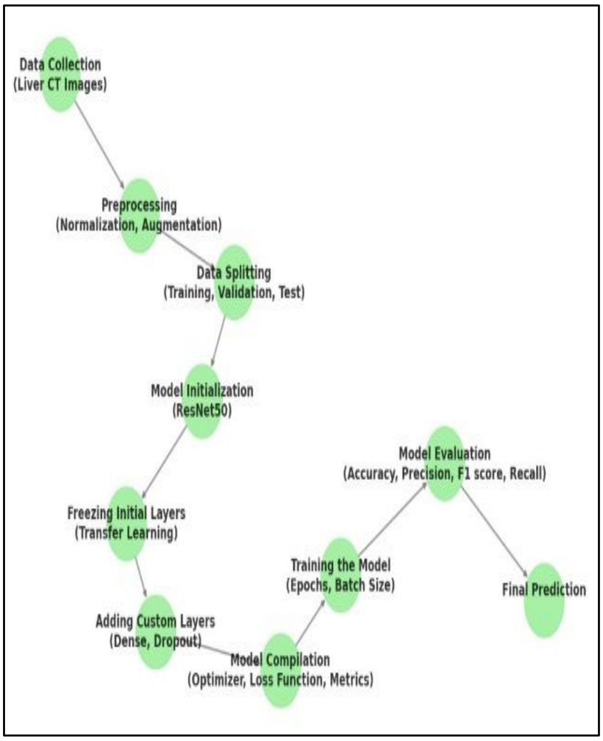

Fig. 2. Proposed methodology.

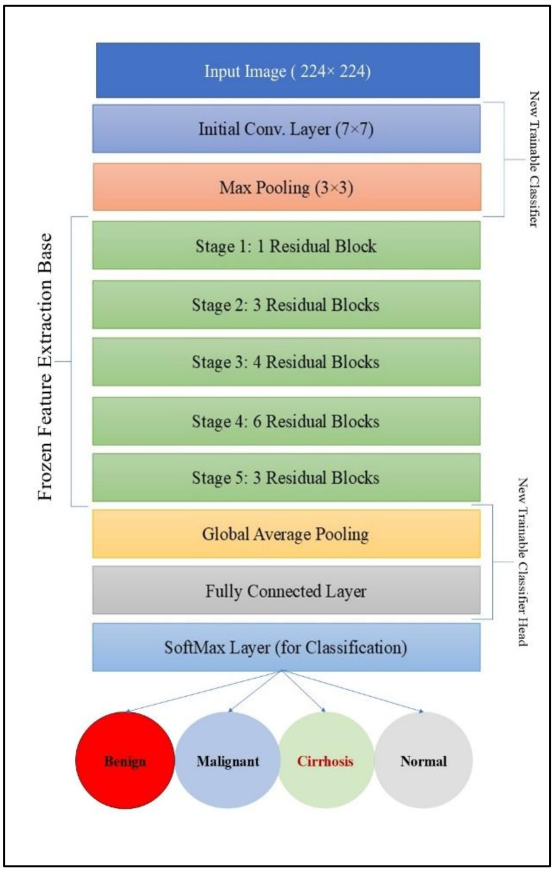

Fig. 3. ResNet-50 Architecture.

The architecture of the ResNet-50 framework can be succinctly summarized as follows:

- Initial Convolutional Layer: This layer applies convolution to the input utilizing 64 filters, each measuring 7 × 7, succeeded by batch normalizing, ReLU activation, and maximum pooling with an initial kernel size of 3 × 3.
- Residual Blocks: A series of residual blocks ensues, each consisting of convolutional layers that augment the amount of feature channels while systematically diminishing the overall dimension of the input. These blocks facilitate the acquisition of residual mappings and assist in alleviating degradation as network depth escalates.
- Global Average Pooling: A global average pooling layer computes the mean of the feature mappings from the last residual block, yielding a fixed-size outputs.
- Fully Connected Layers: The pooled features are transmitted over several fully connected (dense) layers. The initial fully connected layer comprises 256 neurons and utilizes the ReLU activation function in conjunction with dropout for regularization. The output layer produces class probabilities after to the application of a softmax activation function.

4.1. Mathematical representation

The ResNet-50 model can be described mathematically as follows:
-Convolution Layer: A convolution operation is applied to the input I using a filter K, followed by a bias term b and a non-linear activation function σ (ReLU in most cases):

$$C = \sigma(K * I + b) \tag{1}$$

where $*$ denotes the convolution operation.
-Batch Normalization.: The output of each convolutional layer is passed through a batch normalization operation to stabilize the learning process by normalizing the activations:

$$\hat{X} = \frac{X - \mu}{\sigma}\gamma + \beta \tag{2}$$

where μ and σ are the mean and standard deviation of the activations, and γ and β are learnable scaling and shifting parameters.
-Residual Block.: Each residual block adds the input X to the output of the convolutional layers:

$$Y = F(X) + X \tag{3}$$

where $F(X)$ represents the set of convolutions and activations applied to X, and the addition operation denotes the residual connection.
-Global Average Pooling: This operation averages the feature map across the spatial dimensions:

$$\hat{F} = \frac{1}{H \cdot W}\sum_{i=1}^{H}\sum_{j=1}^{W} F(i,j) \tag{4}$$

where H and W represent the height and width of the feature map, and $F(i,j)$ represents the feature map values at position (i,j).
-Fully Connected Layer: A dense layer computes the output O using the weights W and bias b:

$$O = \sigma\left(W \cdot \hat{F} + b\right) \tag{5}$$

where σ is the activation function (ReLU for intermediate layers, softmax for the output layer).
The layers of the proposed model are illustrated in Table 1. Total Trainable Parameters: ~23.5M

Table 1. The model architecture Layers.

Layer No.	*Layer Type*	*Output Shape*	*Number of Parameters*
1	Input Layer	(224, 224, 3)	0
2	Conv2D (7x7, 64 filters, stride=2)	(112, 112, 64)	9,408
3	BatchNormalization	(112, 112, 64)	256
4	ReLU Activation	(112, 112, 64)	0
5	MaxPooling2D (3x3, stride=2)	(56, 56, 64)	0
6-49	ResNet-50 Convolutional Layers (Residual Blocks)	(7, 7, 2048)	~23M+ parameters
50	GlobalAveragePooling2D	(2048)	0
51	BatchNormalization	(2048)	8,192
52	Dropout (0.5)	(2048)	0
53	Dense (256 neurons, ReLU)	(256)	524,544
54	Dropout (0.5)	(256)	0
55	Dense (3 neurons, Softmax)	(3)	771

4.1.Model optimization and training

This study describes the implementation of an optimization framework for the classification of liver diseases using CT images. The modified ResNet-50 architecture performance was attempted to be maximized.
The modified ResNet-50 model was optimized using Adam optimizer with an initial learning rate of 1×10^{-4} and β_1, β_2 momentum parameters set to 0.9 and 0.999 respectively.

A piecewise constant learning rate scheduler that reduces the learning rate by a factor 0.1 every 20 epochs was applied to aid with fine-tuning in the later stages. The model was trained in 80 epochs with a batch size of 46 resulting in 104 iterations per epoch.
The parameter update in Adam can be conceptually expressed in a condensed general form as follows:

$$\theta_{t+1} = \theta_t - \alpha \cdot \frac{(1-\beta_1)\cdot g_t}{\sqrt{(1-\beta_2)\cdot g_t^2 + \varepsilon}} \tag{6}$$

where:
- θ_t represents the model parameters at time step t,
- g_t is the gradient of the loss with respect to θ_t,
- α is the learning rate,
- ε is a small constant added for numerical stability (typically 10^{-8}).

The Sparse Categorical Cross-Entropy loss function is the most suitable for multi-class classification tasks with integer encoded labels. In order to mitigate some degree of overfitting and stabilize learning, we implemented Dropout layers at a rate of 0.5 and batch normalization, while early stopping with a patience of 10 epochs and model checkpointing ensures efficient training and optimal weight capturing.

5. Results and Discussion
5.1. Model Evaluation

After training, the model was evaluated on the test dataset, and the following performance metrics were recorded:

1) **Accuracy**: The model attained an accuracy of 99.3% on the test set, demonstrating the ResNet50 model's remarkable performance in categorizing liver disease images, as illustrated in figure 4.

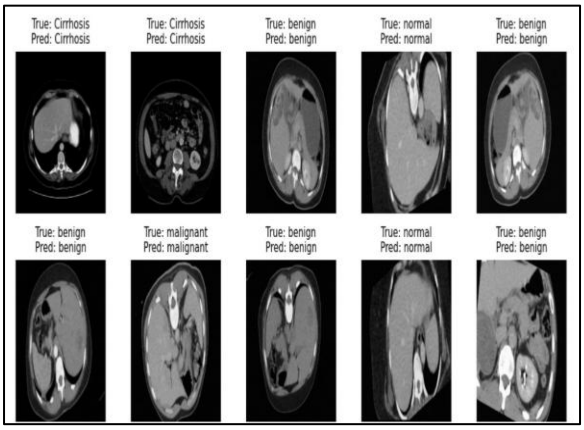

Fig. 4. Prediction results for different classes of liver disease.

2) **Confusion Matrix**: The confusion matrix was generated to evaluate the model's ability to distinguish between the classes. The model did well in every class, with very few incorrect classifications, particularly when it came to differentiating between benign and malignant tumors. As seen in Figure 5.

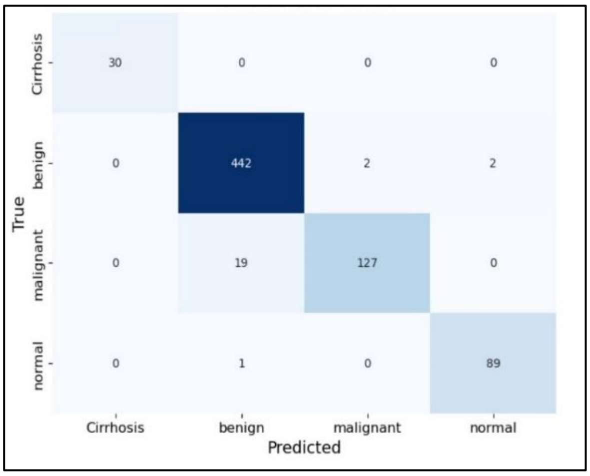

Fig. 5. Confusion matrix of proposed ResNet-50 approach

3) **Classification Report**: Precision, recall, and F1-score metrics were computed for each class, providing insight into the model's performance beyond just accuracy. The model achieved balanced performance across all classes, with particularly high precision for the *malignant* class. As shown in table 2.

Table 2. Liver cancer classification results of Modified ResNet-50 technique

Class	*precision*	*recall*	*f1-score*	*support*
Cirrhosis	1.00	1.00	1.00	30
benign	0.96	0.99	0.97	446
malignant	0.98	0.87	0.92	146
normal	0.98	0.99	0.98	90

5.2.Hyperparameter tuning

The hyperparameter tuning process revealed that increasing the number of dense units improved the model's validation accuracy, which confirms the importance of the number of neurons in fully connected layers in optimizing model performance. An efficient Hyperband search algorithm was utilized for hyperparameter tuning, where the configurations for dense units (128, 256, and 512), dropout rates (0.3 to 0.7), and learning rate decay parameters (0.1 to 0.5) were optimally set. The best performance in validation metrics was achieved at a configuration of dense units equal to 256, dropout of 0.5, and a decay factor of 0.1.

Table 3. Comparison of the proposed accuracy of the model to existing methodologies.

Study	***Model / Method***	***Accuracy / Dice Score***	***Modality***
Alahmer et al. (2016)	SVM + Feature Extraction	98% accuracy	CT
Christ et al. (2017)	CFCN + 3D CRF	94% Dice	CT / MRI
Wang et al. (2018)	Modified ResNet + TL	91.2% accuracy	CT
Shukla et al. (2022)	CFCN + Shape Modeling	94.21% accuracy	MRI
Stephe et al. (2024)	TAGN and ViT-GRU model	84.65% accuracy (TAGN), 97.57% accuracy	CT
Appati et al. (2024)	Multiattention ResUNet + U-Net (Self-Attn)	Dice: 0.92 (liver), 0.83 (tumor)	CT
Proposed ResNet-50	Modified ResNet-50	**99.3%** accuracy	CT

5.3.Comparison to Other Models

The Modified ResNet50 performed well compared to other CNN architectures like VGG16 and InceptionV3 in preliminary tests, as demonstrated in the subsequent table 3. The use of residual connections in ResNet50 allowed it to effectively train deeper layers, resulting in better feature extraction from liver disease images.

Regarding classification accuracy, the Modified ResNet-50 model surpassed almost all of the referenced models. It achieved 99.3% accuracy in the test set and was able to differentiate between four liver tissue classes (benign, malignant, cirrhotic, and normal) with notable precision and recall. The difference in performance is especially striking compared to older techniques of machine learning, which often depend on handcrafted features and do not take advantage of the hierarchical structure of features learned using deep convolutional neural networks.

6. Discussions and Recommendations

This study focused on creating and evaluating the Diagnostic performance of a Modified ResNet-50 deep Convolutional Neural Network (CNN) model for liver disease classification using CT scan images. The model's results showed that its training accuracy, validation accuracy, and test accuracy were 99.1%, 96.4%, and 99.3%, respectively. The model was able to correctly classify the diseases into benign, malignant, cirrhosis, and normal categories. ResNet-50 architecture provided the medical images with elaborate details owing to its residual connections which helped the model achieve high precision and recall for benign and malignant cases. Furthermore, the model was able to achieve better generalization with careful selection of hyperparameters and implementation of data augmentation techniques like rotation, flipping, and zooming. The data obtained after this research support the idea of using deep learning algorithms like ResNet-50 neural network as the backbone for automated systems for liver disease detection and diagnosis. This method has the potential to bring significant impact towards clinical application for primary diagnosis and screening, especially considering the high accuracy and balanced performance for all classes received from the model.

7. Future Work

In the future, work could tackle class imbalance with oversampling or losses with class weights. Adding patient demographic and genetic multi-modal data may enhance accuracy of the diagnosis. Using some techniques to increase model interpretability would improve trust from clinicians. Transferring learning from a pre-trained model may be more efficient for smaller quantities of data. Validation in real-world scenarios utilizing external datasets is essential to verify the model's accuracy. To enhance the model's applicability in medical care, its integration with clinical systems and the execution of longitudinal research could be pursued.

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