Research Article

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A transfer learning approach for the classification of liver cancer

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Abstract

Problem – The frequency of liver cancer is rising worldwide, and it is a common, deadly condition. For successful treatment and patient survival, early and precise diagnosis is essential. The automated classification of liver cancer using medical imaging data has shown potential outcome when employing machine and deep learning (DL) approaches. To train deep neural networks, it is still quite difficult to obtain a large and diverse dataset, especially in the medical field.

Aim – This article classifies liver tumors and identifies whether they are malignant, benign tumor, or normal liver.

Methods – This study mainly focuses on computed tomography scans from the Radiology Institute in Baghdad Medical City, Iraq, and provides a novel transfer learning (TL) approach for the categorization of liver cancer using medical images. Our findings show that the TL-based model performs better at classifying data, as in our method, high-level characteristics from liver images are extracted using pre-trained convolutional neural networks compared to conventional techniques and DL models that do not use TL.

Results – The proposed method using models of TL technology (VGG-16, ResNet-50, and MobileNetV2) successfully achieves high accuracy, sensitivity, and specificity in identifying liver cancer, making it an important tool for radiologists and other healthcare professionals. The experiment results show that the diagnostic accuracy in the VGG-16 model is up to 99%, ResNet-50 model 100%, and 99% total classification accuracy was attained with the MobileNetV2 model.

Conclusion – This proves the improvement of models when working on a small dataset. The use of new layers also showed an improvement in the performance of the classifiers, which accelerated the process.

Keywords: liver cancer classification, deep learning, transfer learning, liver CT, VGG-16, ResNet-50, MobileNetV2

1 Introduction

Liver cancer is a potentially fatal condition. However, liver cancer death rates can be reduced when it is discovered early. Many functions that are crucial for good health are handled by the liver [1]. One of these functions is the transformation of food into protein, both of which are essential for digestion. Chemicals that were inhaled and may be hazardous are removed from the body. By using vitamins, carbs, and minerals kept

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in the liver's reserve, it obliterates many nutrients obtained through the digestive system and restricts the release of cholesterol [2]. The tissues of the body are built of minuscule units called cells. The usual course of events is for cells to multiply and divide to produce new cells. A new cell must be created to replace an outdated or damaged one. If the tissues of damaged or dead cells that have been expelled from the body are not eliminated, nodules and tumors may form. Malignant and benign tumors can also develop in the liver. Compared to benign tumors, malignant tumors pose a greater threat to health [3]. Early detection dramatically improves liver cancer treatment options and prognosis. When liver cancer is found early, before it has spread to other organs, the chances of a successful therapy increase. Treatments that are curative, including surgery, liver transplantation, or specialized therapy like radiofrequency ablation, are more effective in curing early-stage liver cancer. In addition, early detection makes less drastic therapeutic procedures possible, enhancing the quality of life for patients. Early-stage liver cancer treatments often have fewer side effects and need shorter recovery time than advanced-stage liver cancer treatments. With prompt identification and efficient treatment, the life expectancy for those with liver cancer can be extended. Patients have a better chance of long-term survival and chronic disease treatment with an early diagnosis, The medical images offer objective, reliable proof for liver illnesses that may be thoroughly analyzed in addition to clinical symptoms and lab test results. Among the mainstays of imaging examinations, computed tomography (CT), magnetic resonance imaging, and ultrasound are regularly employed modalities [4]. However, radiologists' expert judgment, which has low sensitivity and probably exhibits observer bias, is used to evaluate the images. The visual examination of such a large number of medical scans is also labor and time intensive. To solve this issue, computer-aided diagnostic (CAD) systems incorporating computer vision and deep learning (DL) have been successfully created in recent years. These methods make imaging interpretation easier than manual segmentation and detection of the images [5]. The DL algorithms, as the core components of artificial intelligence, are gradually applied in CAD, negating the need for manual customization in contrast to conventional machine learning methods [6,7], which are primarily based on manually created visual descriptors and typically not optimal for specific tasks. In this article, a fine-tuning model is proposed based on DL [8] and transfer learning (TL) techniques to classify the cases from CT scan. When used to classify tumors, TL [9] is a machine learning technique where a model trained on one task is adapted for a second related activity, has various benefits:

1. Increased accuracy: TL uses information from one dataset to another, improving the model's ability to accurately classify different cancer kinds. Pretrained models have acquired helpful features from huge datasets, which can be valuable in comprehending intricate patterns in cancer data.
2. Lessened training time and resources: creating DL models from scratch may be time and resource consuming, especially for challenging tasks like cancer classification. Due to the model starting with prelearned features, TL considerably decreases the training time and resources necessary.
3. Managing small datasets: Because of issues with data gathering and privacy, medical datasets, notably those about cancer, frequently have a small size. Due to the fact that the model learns generic features from a bigger dataset and then customizes them for the particular cancer dataset, TL enables the model to generalize well, even with tiny datasets.
4. Feature extraction and understanding: TL models can act as feature extractors by drawing attention to crucial elements in the data that help classify cancer. This not only helps with precise forecasts but also sheds light on the characteristics that are important for classifying various tumors.
5. Adaptability to multimodal data: Imaging, genetic, and clinical records are just a few examples of the various types of datasets that are frequently used in cancer research. TL models are flexible in handling multimodal datasets because they may be trained on one type of data and then quickly expanded or modified to accommodate and classify other types of data.
6. Continuous learning: As new data become available, TL models can be continuously updated and improved. This flexibility allows the model to include the most recent developments in cancer research without necessitating a total retraining from scratch, ensuring that it remains accurate and relevant.
7. Results that can be interpreted: TL models, particularly those built on convolutional neural network (CNN) architectures, can reveal which areas or aspects of images or data are crucial for classification. In medical applications, where comprehension of the assumptions underlying forecasts is key, this interpretability is essential [10,11].

In conclusion, the efficiency and effectiveness of cancer classification models are considerably increased using TL technology, making them extremely useful for cancer research and diagnosis. Therefore, the main goal of this article is to create an intelligent system that will help physicians identify the type of liver cancer. Below is a summary of the most important contributions of this study:

1. To use a new dataset from the Radiology Institute in Iraq's Baghdad Medical City.
2. To employ three TL learning models (VGG16, ResNet50, and MobileNetV2), along with modifications to structural models, to enhance results and accuracy.

The remaining sections of the paper are organized as follows. Section 2 presents the related works, while Section 3 presents the proposed method, results and discussions are presented in Section 4, and finally, the conclusions, as well as a few suggestions for future research, are presented in Section 5.

2 Related works

This section reviews the literatures that used DL, to detect and classify liver cancer. Since DL has semi-pioneer and requires a lot of data, it can be argued that it has become a semi-pioneer in many scientific, security, and other domains, including healthcare. These are some researches pertaining to this topic in Table 1.

3 Materials and methods

This section explains the general structure of the liver cancer classification system used to enhance the performance of DL classifiers for the classification of liver cancer, as illustrated in Figure 1.

3.1 Data description

The dataset for the article was gathered from a CT scan from the Radiology Institute in Baghdad Medical City, Iraq, with an average resolution of 500 × 500 pixels; the collection consists of 700 PNG images. The images are divided into three groups: normal (231 images), benign (364 images), and malignant (105 images). The types of benign are Hydatid cysts, hemangioma, and simple cysts. Types of cysts are CE1, CE3a, CE4, and CE5. Malignant liver lesions often have an ill-defined margin with the surrounding hepatic parenchyma, whereas benign masses tend to have a well-defined parenchymal interface. There are two types of benign tumors in the paper: hemangioma and cyst. The first cannot be removed surgically; only it is followed up from time to time. As for the cysts, if they are in the first, second, or third stage, they are surgically removed. If they are in advanced stages, they are not removed because they are calcified. There are two stages in cancer cases: the primary stage and the secondary stage. The first can be surgically removed; however, the second has spread and cannot be removed due to metastasis. Only chemotherapy will be effective in treating it. Figure 2 shows some of the images from each class.

3.2 Pre-processing

Image pre-processing is the initial step in exhibiting many important image features for later use. Images of liver cancer are only slightly improved during the pre-processing step. The following subsections include details of the steps that were used in the first step.

Table 1: Previous studies to classify liver tumors using DL

N	Author(s)/year	Methodology	Dataset	Results	Limitations
1	Krishan et al. [12] 2020	The ensemble model that has been created consists of six different models: The various types of classifiers are Decision Tree, Adaptive Boosting (AdaBoost), Random Forest (RF), Support Vector Machine (SVM), Generalized Linear Model (GLM), and Neural Network (NN)	844 different forms of aberrant liver data (483 of which showed the secondary liver cancer type MET and 361 showed the primary liver cancer type HCC), compared to 794 normal liver images	The accuracy for tumor classification ranges from 76.38 to 87.01%	– Small sample size: the study may have a small sample, which could affect how well the results apply to a larger population – Lack of external validation: Because the study may not have received external validation, it may be more difficult to verify the precision and generalizability of the findings
2	Messaoudi et al. [13] 2020	A CNN technique is used	The data are collected from nine patients	The newly constructed CNN model achieved an accuracy level of 90%	Limited scope: The study may have a narrow focus, concentrating exclusively on identifying and categorizing liver cancer, which may limit its generalizability
3	Othman et al. [14] 2020s	DL model employing CNNs	LiTS17 dataset, which serves as a training instance for liver lesions and tumors. There are 130 CT scans in DCOM format. 3D-IRCADb-01 Dataset contains 20 3D CT scans from 20 distinct individuals, 75% of whom showed liver cancers. Each image size is 512 by 512 pixels, and the average liver density ranges from 40 to 135	The best outcomes that they were able to acquire for this study had an accuracy value of 99.50%	The research was constrained by the vast array of weight parameters, which increased model size and inference time. Additionally, the LITS and 3D-IRCADb-01 datasets utilized in the study did not have samples that were nationally representative; therefore, it is impossible to compare the performance metrics in these datasets to national estimates of radiologists' sensitivity and specificity
4	Constantinescu et al. [17] 2021	CNNs with various topologies	A set of 629 images that includes two different types of liver imaging	Accuracy is 93.23%, sensitivity is 89.9%, and precision is 96.6%	The dataset size is quite modest, and a higher sample size is required to increase the deep learning network's accuracy and confirm the applicability of the suggested strategies A future study will compare the performance of the diagnosing methods with that of specialists Even though studies suggest that the specificity and sensitivity of ultrasonography are comparable to those of histology, liver biopsy should be used as the gold standard to support ultrasound diagnosis if you want more reliable results

(Continued)

Table 1: *Continued*

N	Author(s)/year	Methodology	Dataset	Results	Limitations
					The results could have been significantly impacted by the fact that the values acquired using the pre-trained CNN were calculated as means of images that were manually chosen by a medical professional
5	Sabir et al. [15] 2022	The 3D-IRCADb01 dataset is used to develop the Res U-Net architecture using CT images	Liver CT scan dataset The 3D CT scans of 10 female and 10 male patients with liver cancer were among 75 female and male cases that were publicly made available by the IRCAD Digestive Cancer Institute. The 3D CT scan is broken into 2D slices that are each 2800 slices thick and have masks for the liver, kidneys, lungs, bones, arteries, and tumors	A DSC value of 0.97% for organ recognition and 0.83% for segmentation methods	– Small sample size, lack of variety in the sample population, potential biases in data collection or analysis, limited generalizability of findings, and potential confounding variables that were not taken into consideration
6	Jasti et al. [16] 2022	The RBF-SVM strategy, the ANN method, and RF method are all used	LiTS17 is a baseline for segmenting liver tumors. The segmentations and data are supplied by numerous clinical locations globally. There are 130 CT scans in the training dataset and 70 in the test dataset	RBF SVM achieved 92.86, 85.71, and 92.86% for accuracy, sensitivity, and specificity respectively, while ANN achieved 91.43, 94.29, and 85.71% for accuracy, sensitivity, and specificity respectively, finally Random forest achieved 88.57, 82.86, and 88.57% for accuracy, sensitivity, and specificity respectively	– Limited sample size or data utilized in the study: The results may not be generalizable because the study may have employed a small sample size or data regarding liver tumors – Potential for overfitting: The study's algorithms may have been too closely tailored to the particular employed dataset, which might hinder their capacity to generalize to new data

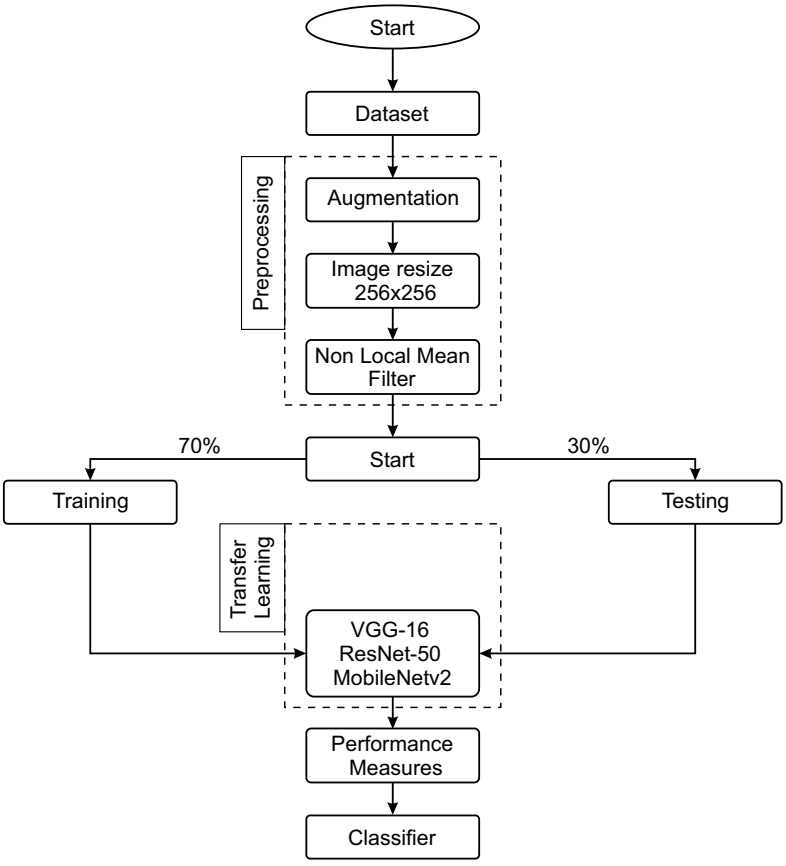

Figure 1: The general structure of the liver cancer categorization system.

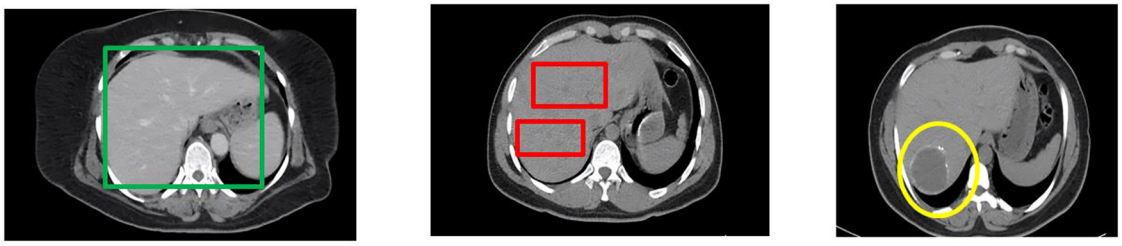

Figure 2: (a) Normal liver, (b) malignant, and (c) benign.

3.2.1 Augmentation

Augmentation, also known as data transformations, is a typical pre-processing approach that involves increasing the dataset and modifying the images in different ways so that the network is able to perceive more kinds of information. By reducing the possibility of overfitting, this approach successfully expands the dataset. In imaging augmentation, scaling, rotation, and other similar alterations are frequently used. The technique of augmentation increases the probability that the model will detect objects of any shape by extending datasets and providing neural networks with a variety of visual variants. For the dataset on liver cancer, data augmentation [18] is used in this study It is also important to note that the dataset is expanded to 1491 images. Rotation is employed in this work as follows.

Rotation range: It is a type of enhancement that helps the network recognize the object in any direction in the image. The max_left_rotation and max_right_rotation control the degree by which the image is rotated, all of the images in this work have been rotated with (max_left_rotation = 5) and (max_right_rotation = 5).

3.2.2 Image resize

The requirement for image scaling in the dataset to a consistent dimension is one of CNN's primary limitations. In this work, the images are resized to the desired size (best practice is 256 × 256).

3.2.3 Non-local mean filter

For image denoizing the non-local means filtering approach was used. Non-local means filtering takes a mean of all pixels in the image, weighted by how similar these pixels are to the target pixel, as opposed to "local mean" filters, which take the mean value of a group of pixels surrounding a target pixel to smooth the image.

3.3 Data splitting

The dataset is divided into two sets: one for training and the other for testing. The validation set of tests is used to assess the effectiveness of the model. The dataset was divided into a training set and a test set with 70 and 30% ratio. the splitting ratio is the best obtained one that comes after testing many ratios.

3.4 TL

When used to classify medical images, many CNN models have been successful. Several popular CNN topologies may be applied; they can be conventional ResNet-50 [19], VGG-16 [24], and MobileNetV2 [25], which will be the main focus of the experiment. We modified the architecture of the models, although some layers are kept frozen, new fully connected layers with random parameters are used in place of the layers from the pre-trained models. We followed the global average pooling (GAP) layer [20] to reduce the spatial dimensions of the output from the base model, a fully connected dense layer with 256 neurons and ReLU activation function [21], and a final dense layer with three neurons (for each class) and SoftMax activation function [22] to output the class probabilities. After defining the model architecture, the models are compiled using the compile function with categorical cross-entropy loss function, Adam optimizer [23], and evaluation metrics such as accuracy, recall, precision, and $F1$-score. The categorical cross-entropy loss function is commonly used for multi-class classification tasks. The Adam optimizer is a popular gradient-based optimization algorithm that is commonly used in DL. The accuracy metric measures the fraction of correctly classified samples, while the recall metric measures the fraction of relevant instances that are retrieved. The inclusion of recall as a metric is particularly useful in imbalanced datasets, where the number of instances for each class is significantly different, this process delivered more accuracy. The new fully connected layers can learn patterns from previously taught convolutional layers through the use of a rather low learning rate. Even without initial training, our models, VGG-16, ResNet-50, and MobileNetV2, were able to detect liver cancer by applying fine-tuning. In the second step, we used a sequential model using TL with the VGG-16, ResNet-50, and MobileNetV2 architecture pre-trained on the ImageNet dataset [26]. The process described above was applied by the following models.

3.4.1 VGG-16

The VGG-16 network that is pre-trained on ImageNet is used. The model we used included all the layers in the network layers, although the layers below are kept frozen, the pre-trained models' layers are replaced with new three-layer GAP pooling layer and two fully connected dense layers. Our optimizer was Adam, as depicted in Figure 3.

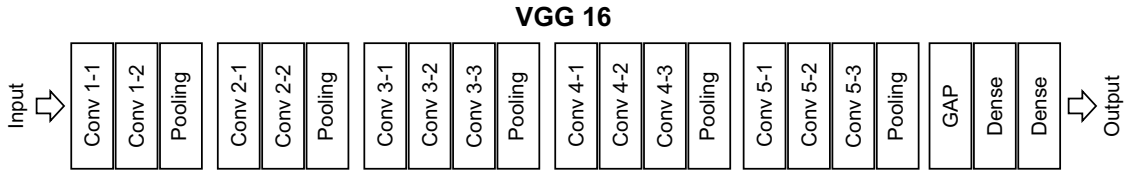

Figure 3: VGG-16 architecture.

3.4.2 ResNet-50

The ResNet-50 network pre-trained was also employed. Every layer in the network layers was included in the model we utilized. Although the layers below are kept frozen, new three-layer GAP pooling layers and two fully connected dense layers are used in place of the pre-trained models' layers. Our optimizer was Adam as shown in Figure 4.

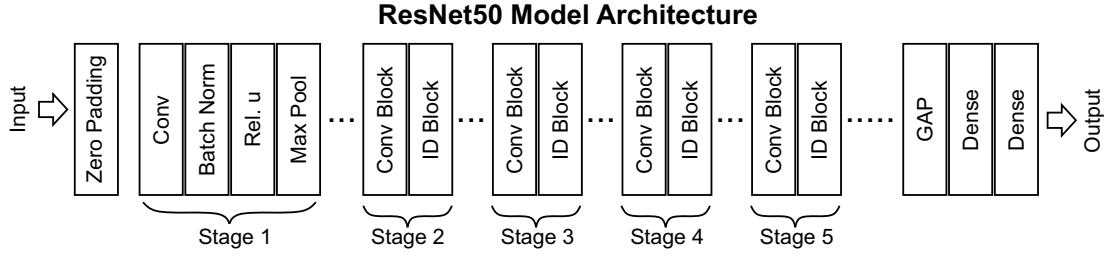

Figure 4: ResNet-50 architecture.

3.4.3 MobileNetV2

The pre-trained MobileNetV2 network was also used. The model we used comprised every layer in the network layers. The pre-trained model layers are replaced with new three-layer GAP pooling layers and two fully connected dense layers while the levels below are maintained frozen with the optimizer Adam as shown in Figure 5.

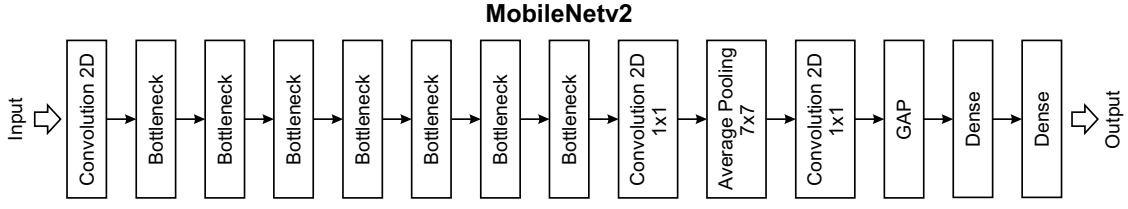

Figure 5: MobileNetv2 architecture.

4 Results and discussion

This section is divided into the following parts: results are provided in Section 4.1; results are compared to related works in Section 4.2; and research limitations are presented in Section 4.3.

4.1 Results

The proposed TL model for liver cancer disease diagnosis is assessed after each epoch. Three pre-trained models were utilized to identify and classify the distinctive features in each liver image. The obtained results for our dataset show a final diagnosis accuracy of 99.10% for the VGG-16 and 99.10 for the MobileNetV2 model. By comparison with the final diagnosis, accuracy was 100% for the ResNet-50 model. Metrics are summarized in Figures 6–11.

	precision	recall	f1-score	support
benign	1.00	1.00	1.00	73
malignant	1.00	1.00	1.00	89
normal	1.00	1.00	1.00	62
accuracy			1.00	224
macro avg	1.00	1.00	1.00	224
weighted avg	1.00	1.00	1.00	224

Figure 6: Classification accuracy using the ResNet-50 model, with support for recall, precision, and *F*1-score.

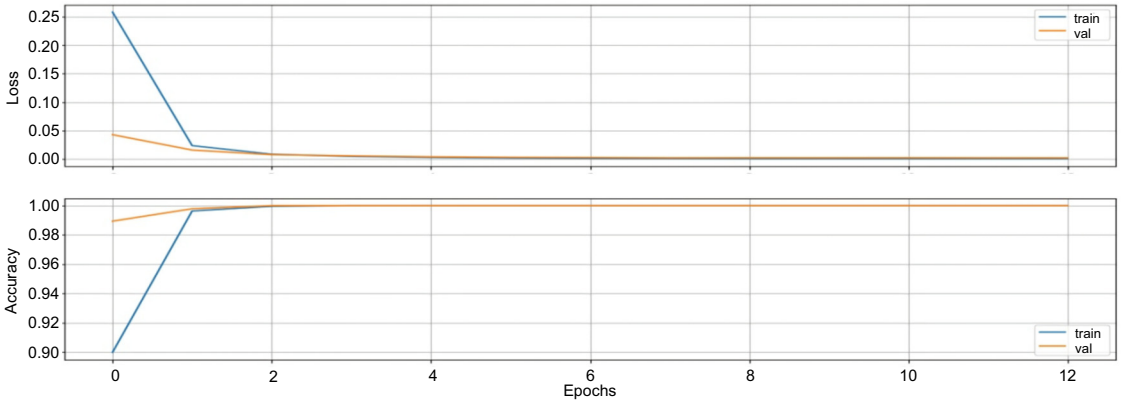

Figure 7: Training progress for ResNet-50.

	precision	recall	f1-score	support
benign	1.00	0.99	0.99	73
malignant	0.99	0.99	0.99	89
normal	0.98	1.00	0.99	62
accuracy			0.99	224
macro avg	0.99	0.99	0.99	224
weighted avg	0.99	0.99	0.99	224

Figure 8: Classification accuracy for VGG-16 model to precision, recall, and *F*1-score.

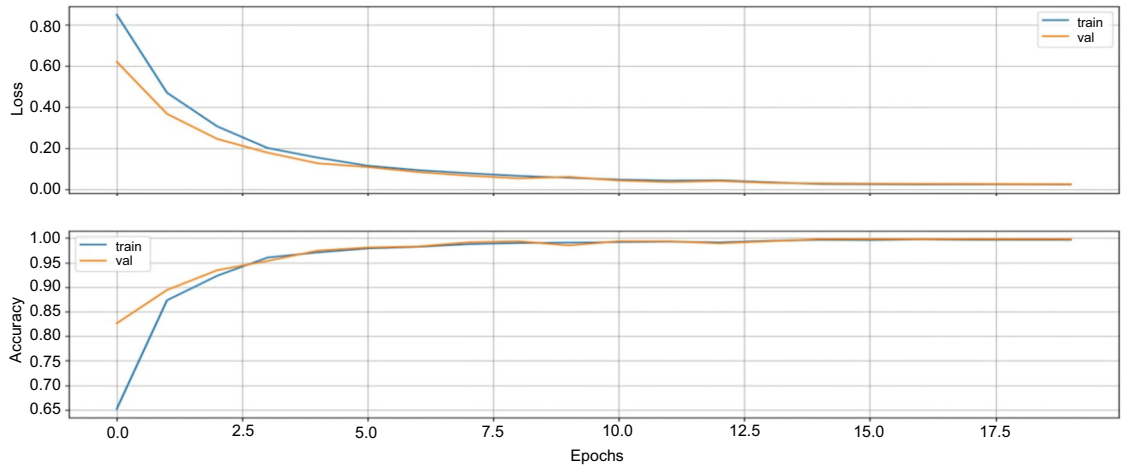

Figure 9: Training progress for VGG-16.

	precision	recall	f1-score	support
benign	0.99	0.99	0.99	73
malignant	0.99	0.99	0.99	89
normal	1.00	1.00	1.00	62
accuracy			0.99	224
macro avg	0.99	0.99	0.99	224
weighted avg	0.99	0.99	0.99	224

Figure 10: Classification accuracy for the MobileNetV2 model to precision, recall, and *F*1-score.

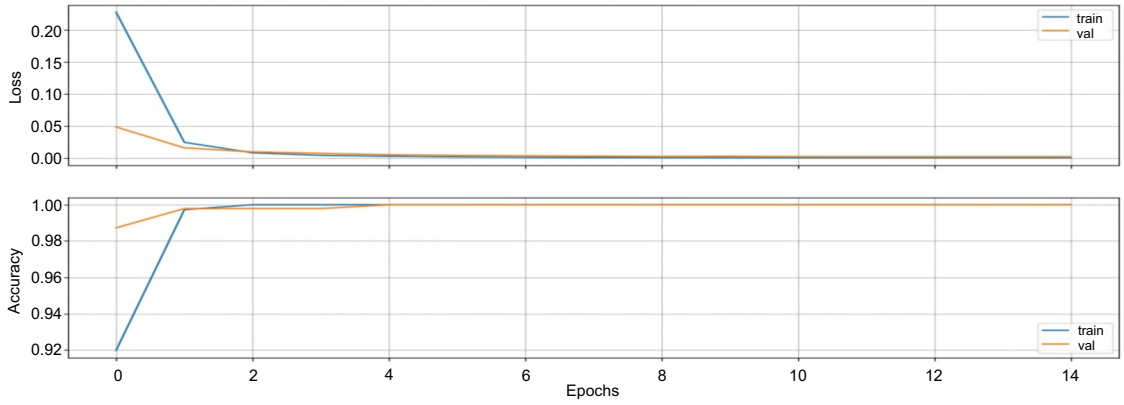

Figure 11: Training progress for MobileNetV2.

We utilized the following metrics: accuracy, recall, and *F*1-score. The below formulas were used to calculate each measurement

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

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \tag{2}$$

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

$$F1\text{-score} = 2 \times \frac{(\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})}, \tag{4}$$

where TP, TN, FP, and FN are the numbers of the true positive, true negative, false positive, and false negative results, respectively.

From Figures 7, 9, and 11, it can be seen that the loss starts with high values while learning is still low and then declines to its lowest value during the most utilized epoch. The classifier has excellent performance because of the validation test's typical behavior, which consistently classifies the training examples. When minimal learning has occurred, the loss starts out high and then decreases to its lowest value, while the learning is increasing and reaching its highest level at the most used epoch. The classifier will perform exceptionally well because of the validation test's normal behavior, which typically identifies the training data. Additionally, the number of epochs varies from one model to another and according to the way the data set is divided. Compared to ResNet50V2 and MobileNetV2, which each utilized 13 epochs, VGG-16 used 20.

4.2 Comparison with related works

The results of the suggested methodology have been compared with the related works, as shown in Table 2, proving the effectiveness of the used methods. In terms of accuracy, precision, recall, and *F*1-score: Resnet-50 achieved 100, 99.10, 99.10, and 100% respectively, while VGG-16 achieved a scoring of 99, 99, 100, and 99% respectively; finally, MobileNetV2 achieved 99, 100, 99, and 99%, respectively. The results of the classification were enhanced by selecting appropriate parameters that changed the model's structure. The advantage of the suggested strategy over related works is in the employing of GAP layer, a fully linked dense layer with 256 neurons and a ReLU activation function and a final dense layer with three neurons were used to minimize the spatial dimensions of the output from the base model. Through the use of a relatively low learning rate of 0.0001, the new fully linked layers can learn patterns from previously taught convolutional layers. Our models, VGG-16, ResNet-50, and MobileNetV2 were able to classify liver cancer even without initial training.

Table 2: Comparison with related works

Classifier	Accuracy (%)	Precision (%)
Six different models: decision tree, Adaboost, RF, NN, SVM, and GLM [13]	76.38–87.01	—
CNN technique [9]	90	—
Hybrid pre-trained models [10]	98.4	73.5
Inception v3 [13]	93.23	96.6
VGG-16 [13]	90.77	91.8
Proposed approach ResNet-50	100	100
Proposed approach VGG-16	99	99
Proposed approach MobileNetV2	99	99.8

4.3 Research limitations

Most research studies have some limitations that can be resolved in later studies. This study's limitations are as follows:

1. Some samples are still incorrectly categorized. To prevent this, more pre-processing might be used.
2. Small sample size: The study's sample size may have an impact on how effectively the findings generalize to a larger population. Because medical data are sensitive and take a long time to collect, it is possible to work on gathering new data, which we are still doing. We will apply it to our upcoming papers.

5 Conclusions and future works

The liver is in charge of several different processes that are crucial to keeping one's health. one of these processes, The liver may develop benign or malignant tumors, two different types of growths. Expertise in this area is necessary to detect small changes in the liver. However, such minute changes might not always be seen by the human eye. A lot of lives could be saved by medical assistance made possible by DL. This motivation led to the use a DL technique, namely the TL to provide a reliable method for identifying cases of liver cancer. In this paper, a collection of procedures is employed to identify liver cancer. This paper assessed the effectiveness of TL using ResNet-50, VGG-16, and MobileNetV2. We observed that the algorithms' best performance was attained. After contributing to altering the models' structure by adding necessary layers and freezing others, a high level of diagnostic precision was obtained., where the proposed models using TL (ResNet-50, VGG-16 and MobileNetV2) obtained an accuracy of 100, 99, and 99%, respectively. As it turns out, modern research techniques such as TL in DL can successfully handle diagnosing issues for physicians. Furthermore, data augmentation improved the amount of training data that was available throughout the training phase, which helped the suggested model avoid the overfitting issue. For future work, based on what we have observed in the outcomes of prior studies and our own discoveries, we suggest trying to extend the dataset size while utilizing other modern algorithms of DL, such as You Look Only One (Yolo) algorithm.

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Ethical approval: This article does not contain any studies involving human participants performed by any of the authors.

Data availability statement: Data sharing is not applicable to this article, as no datasets were generated or analyzed during the current study.

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