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Liver disease prediction using machine learning

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Abstract: This study proposes a deep learning-based approach to classify liver histopathological images into four categories: ballooning, fibrosis, inflammation, and steatosis, using the VGG16 convolutional neural network (CNN). The VGG16 model, pre-trained on ImageNet and fine-tuned on a liver disease dataset, is used for feature extraction and classification. Data augmentation techniques address challenges of limited medical images. The model is evaluated using precision, recall, F1-score, and accuracy metrics. This approach demonstrates the potential of deep learning to support pathologists in diagnosing liver diseases, offering a reliable and automated tool for healthcare professionals.

I. INTRODUCTION

Liver disease is a global health issue that affects millions, contributing to high morbidity and mortality.
The liver plays a critical role in detoxification, digestion, energy storage, and metabolic regulation.
Common liver diseases include hepatitis, fatty liver disease, cirrhosis, liver cancer, and genetic disorders. Chronic damage can lead to fibrosis, cirrhosis, liver failure, or liver cancer. Early detection and treatment are crucial to prevent severe progression.

II. RELATED WORK

S. Bharathi et al. (2022) proposed a deep convolutional neural network (CNN) model for efficient liver disease prediction using biopsy images. The study focused on nonalcoholic fatty liver disease (NAFLD) and its progression to conditions like nonalcoholic steatohepatitis (NASH), fibrosis, and hepatocellular carcinoma (HCC). The CNN model achieved a 96.8% generalization ability, with AlexNet being the most efficient architecture. K. Pathak and D.K. Singh (2022) explored the use of machine learning algorithms like SVM, KNN, and neural networks for early liver disease detection, emphasizing the importance of early diagnosis using various techniques to improve accuracy and precision.

III. METHODOLOGY

A convolutional neural network (CNN)[1][4][5] is a deep neural network framework, in which every neuron will be connected to a region of neurons below it that allows handling of less amount of weights and it is mostly applied in visual imagery for classification and detection problems. It is a version of multilayer perceptrons. The name itself indicates that the network is employed with a mathematical operation called Convolution in order to extract and learn features from the images by the network.

A CNN usually consists following layers:

- Convolutional layer
- Rectified Linear Unit layer
- Pooling layer
- Fully Connected layer

1.Convolutional layer:
The Convolutional layer is can be considered as a building block of a Convolutional Neural Network as it does most of the computational heavy lifting. The network extracts and learns most of the features in this layer. The image is represented as a matrix. A filter that is used as a feature matrix is slide along the image matrix to obtain the convolved feature map. Many different operations can be performed to extract different features by changing the values in the filter matrix.

The basic convolution operation can be depicted below: Overlay the filter to the input, perform element wise multiplication, and add the result. Move the overlay right one position and do the same calculation above to get the next result.

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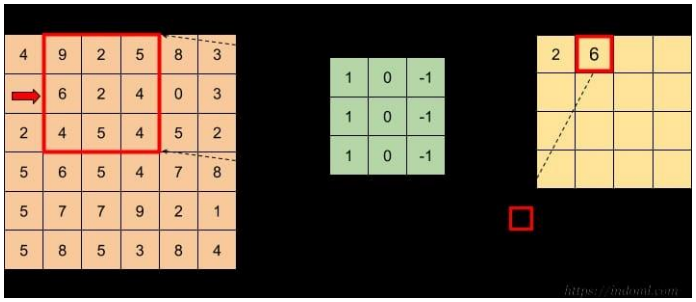
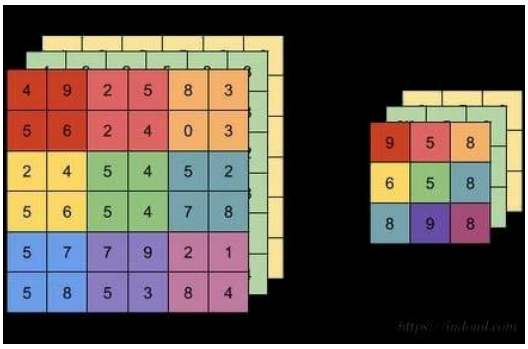
Stride tells us how many cells the filter is to be moved in the input to calculate the next cell in the result. Padding uses a convolutional layer without shrinking the height and width of the volumes. This is important for building deeper networks, since otherwise the height or width would shrink as we go to deeper layers. The output dimension is calculated with the following formula:

where the symbols denote math. Floor() operation.

1.1 Rectified Linear Unit layer:
It is an activation function in which it activates a node if the input is above a threshold and if the input is less than or equal to 0 then the output will be 0.The generated feature map is called as rectified feature map. It maintains a linear relationship with the dependent variable and also introduces non-linearity in the network.



1.2 Pooling layer:
The dimensionality of the feature map is reduced to get shrinker maps that reduces the parameters, weights and computations. Pooling can be Max, Average or Sum Pooling from the rectified and downsized feature map. Number of filters in convolution layer will be same as the number of output maps from pooling. It makes the network invariant to transformations, distortions and translations in the input image.



1.3 Fully Connected layer:
This is the final layer where the actual classification takes place. It uses a SoftMax activation function. The purpose of the fully connected layers is to use features obtained to classify the data into various classes based on the dataset.

The Convolutional Neural Network is a kind of forward-looking organization created by the science framework, where one neuron is arranged to answer an extremely huge region. to be solid in the cutting-edge comprehension of the construction of the imaging framework [21]. At the point when the neuron has similar boundaries used to associate the previous parts, in better places, there is an inaccessible adjustment. This permits CNN to get the district's environmental factors, paying little mind to estimate, area, direction, or other picture highlights. Furthermore, CNN crosses limits that diminish the quantity of preparation stages contrasted with full-line associations [26]. The development of the Convolutional Neural Network, as displayed in Figure 1, is a huge organization of interior muscles comprising of a progression of areas. Coming up next is a rundown of our most famous pages in the Convolutional Neural Network. The secret parts are normally roundabout, trailed by an initiation layer, some of which are negative.

Figure 1 shows the critical parts of the CNN store and comprise of three principle parts: combination, pivot, joining, and full mix. 1 Confirmation segment: This part acknowledges an exceptionally input picture, appropriate for network preparing, and changes it over to an element map utilizing a channel or Convolutional start. The channel is utilized in this segment through the estimations. 2 Partitioning: The primary capacity of this level is to lessen the size and aspects

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of the grid, so this worth is given beneath the Convolutional card. This sheet moves the channel to the Convolutional layer yield and works out the most extreme worth or weighted normal. 3 Complete: The reason for this part is to lay out the consequences of the past two segments as a mark. This page utilizes the sofmax layer to get the worth somewhere in the range of 0 and 1, so it utilizes the Package Normalization technique to speed up and decrease the overabundance. Cellular breakdown in the lungs screening utilizing profound CNN comprises of two phases. The primary stage performs pre-handling activities proper to DCNN picture preparing and handling, so it is feasible to obliterate the highlights, while the subsequent stage performs CT imaging, deciding if the hub type is positive or negative.

Fig.2. DCNN for lung cancer nodule identification.

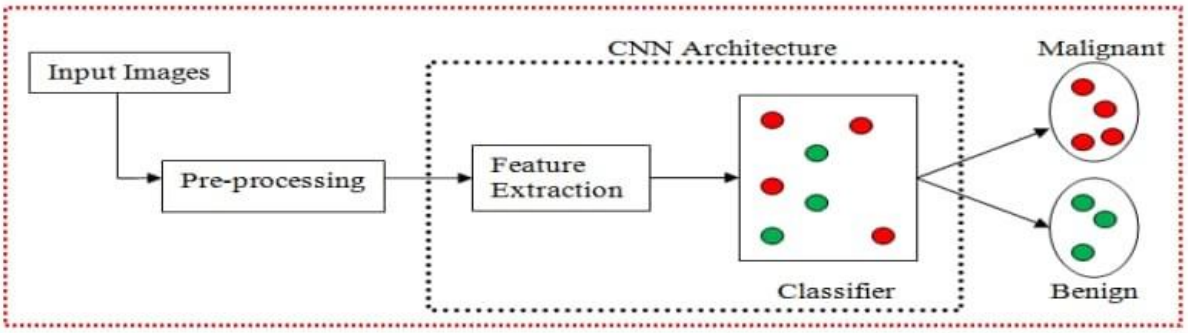

Fig. 1.Flow Chart Diagram

1.4 Training a deep CNN

The consecutive calculation utilizes a 256x256x3 CT picture to prepare the CNN Deep. It comprises of two stages: the preparation stage and the pilot stage. In the primary stage, DCNN is prepared utilizing CT imaging, and 900 pictures are utilized to instruct whether lung relocate a medical procedure is malignant or non-dangerous. The organization is utilized as a plan to analyze and treat disease in the trial class of mysterious pictures. By resizing the organization, it is feasible to get a DICOM picture, as there are no properties to the pictures that are prepared and tried in the DICOM design. An all-around arranged proposition can be carried out with cautious thought.

1.5. Performance Measures parameters

It is feasible to dissect the presentation of clinical imaging utilizing ongoing analytic standards, misfortunes, and assessed time.

· Reality: this is quite possibly the main standard for assessing an example. It gives precisely the number of pixels from the given pictures.

· Misfortune Function: A brain network mistake can be anticipated by a misfortune determined by a misfortune work. There is one more method for estimating network measurements.

· Assessed time: The time expected to finish the computation cycle or its activity. Assuming that the interaction is straightforward, the time it takes to foster it will be more limited than the difficult work of computing the time.

Rescaling: Normalize image pixel values by dividing by 255 to scale them between 0 and 1. Image Resizing: Resize all images to the target size of 224x224 pixels to match the VGG16 input requirement.

Data Augmentation: Apply transformations like rotation, width/height shifts, zooming, horizontal flipping, and brightness adjustments to increase the variability of training images.

Validation Split: Divide the dataset into training and validation sets, using 80% for training and 20% for validation.
Batching: Load images in batches of 32 to optimize memory usage and speed up training.

One-Hot Encoding: Convert categorical labels into one-hot encoded format for multi-class classification.

# Data Augmentation datagen = ImageDataGenerator(
rescale=1./255, rotation_range=30, width_shift_range=0.2, height_shift_range=0.2, shear_range=0.3, zoom_range=0.3, horizontal_flip=True, brightness_range=[0.8, 1.2], fill_mode='nearest', validation_split=validation_split

MODEL TRAINING:

Activation Layer-It produces a single output based on the weighted sum of inputs

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• Pooling Layer-Pooling layers section would reduce the number of parameters when the images are too large. Spatial pooling (also called subsampling or down sampling) reduces the dimensionality of each map but retains important information. Spatial pooling can be of different types: Max Pooling – taking the largest element in the feature map Average Pooling - taking the average of elements in the feature map

Sum Pooling – taking the sum of all elements in the feature map
Fully Connected Layer-The layer we call as FC layer, we flattened our matrix into vector and feed it into a fully connected layer like a neural network. the feature map matrix will be converted as column vector (x1, x2, x3, …). With the fully connected layers, we combined these features together to create a model.

Forclassifying input image into various classes based on training set.
Dropout Layer-It prevents nodes in a network from co-adapting to each other.

VGG16
Architecture: Comprises 13 convolutional layers and 5 max pooling layers.Filter Size: Uses 3×33 \times 33×3 convolutional filters to capture fine details.Downsampling: Max pooling layers reduce dimensionality by taking maximum values in 2×22 \times 22×2 regions.Fully Connected Layers: Ends with 3 fully connected layers for high-level reasoning.Transfer Learning: Often uses pre-trained weights from ImageNet for better performance on new tasks.

MODEL TESTING:
Accuracy Formula:
Explanation: Measures the proportion of correctly predicted instances out of the total instances.
Confusion Matrix
True Positives (TP)
True Negatives (TN)
False Positives (FP)
False Negatives (FN)
Precision
Formula

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Predictions}}$$

Explanation: Measures the accuracy of positive predictions. High precision indicates a low false positive rate. Recall (Sensitivity) Formula:

$$\text{Precision} = \frac{TP}{TP + FP}$$

Explanation: Measures the ability of the model to identify all relevant instances. High recall indicates a low false negative rate.
F1 Score
Explanation: Harmonic mean of precision and recall, useful for imbalanced classes.

$$\text{Recall} = \frac{TP}{TP + FN}$$

IV. RESULT

· Early Training: In the initial epochs (e.g., 1-5), both training and validation accuracy increase rapidly. This indicates that the model is learning quickly from the training data.

· Convergence: Around epoch 10, the training accuracy plateaus or starts to increase slowly, while the validation accuracy continues to improve but at a slower rate. This suggests that the model is starting to overfit.

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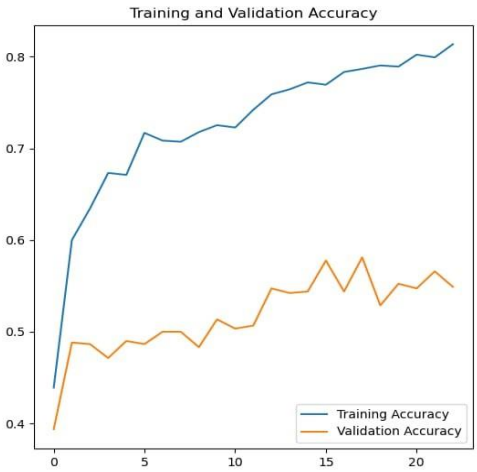
· Overfitting: By epoch 20, the training accuracy has reached a high value (0.85), but the validation accuracy has started to decline (from 0.78 to 0.75). This is a clear sign of overfitting, where the model is becoming too specialized to the training data and struggles to generalize to new examples.



V. CONCLUSION

This study presents a deep learning approach using the VGG16 convolutional neural network for classifying liver histopathological images into four critical conditions: ballooning, fibrosis, inflammation, and steatosis. By leveraging transfer learning from the ImageNet dataset and fine-tuning the model with a specialized liver disease dataset, we achieved improved performance in classifying complex liver conditions.Extensive data augmentation techniques were employed to enhance the diversity of the training dataset, addressing the limitations of medical image availability. The model's effectiveness was evaluated using precision, recall, F1-score, and accuracy metrics, demonstrating its potential to assist pathologists in diagnostic decision-making.Our findings highlight the promise of deep learning in medical image analysis, suggesting that the VGG16 model could serve as a reliable and scalable tool for improving liver disease diagnosis and management in clinical settings. Future research should focus on validating the model in diverse clinical environments and exploring other architectures to enhance diagnostic accuracy further.

REFERENCES

[1]. M. Abdar, M. Zomorodi-Moghadam, R. Das and I.H. Ting, "Performance analysis of classification algorithms on early detection of liver disease", Expert Syst. Appl, vol. 67, pp. 239-251, 2017.

[2]. Gatos, S. Tsantis, S. Spiliopoulos, D. Karnabatidis, I. Theotokas, P. Zoumpoulis, et al., "A Machine-Learning Algorithm Toward Color Analysis for Chronic Liver Disease Classification", Employing Ultrasound Shear Wave Elastography. Ultrasound Med. Biol, vol. 43, pp. 1797-1810, 2017.

[3]. Y. Kawano and D.E. Cohen, "Mechanisms of hepatic triglyceride accumulation in non-alcoholic fatty liver disease", J. Gastroenterol, vol. 48, pp. 434-441, 2013.

[4]. R.J. Wong, M. Aguilar, R. Cheung, R.B. Perumpail, S.A. Harrison, Z.M. Younossi, et al., "Nonalcoholic steatohepatitis is the second leading etiology of liver disease among adults awaiting liver transplantation in the United States", Gastroenterology, vol. 148, pp. 547-555, 2015.

[5]. Y.L. Thian, A.M. Riddell and D.M. Koh, "Liver-specific agents for contrast-enhanced MRI: Role in oncological imaging", Cancer Imaging, vol. 13, pp. 567-579, 2013.

[6]. R. Banerjee, M. Pavlides, E.M. Tunnicliffe, S.K. Piechnik, N. Sarania, R. Philips, J.D. Collier, J.C. Booth, J.E. Schneider, L.M. Wang et al., "Multiparametric magnetic resonance for the non-invasive diagnosis of liver disease", J. Hepatol, vol. 60, pp. 69-77, 2014.