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Detecting liver cancer from MRI using deep learning

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Abstract:

Patients' chances of survival can be increased by early detection and treatment of liver cancer. The most comprehensive information for the differential diagnosis of liver cancers comes from dynamic contrast-enhanced MRI. However, as MRI diagnosis is influenced by personal experience, deep learning might offer a fresh approach to diagnosis. In order to categorize liver cancers based on improved MR images, unenhanced MR images, clinical data including language and laboratory test results, we employed convolutional neural networks (CNNs) to create a deep learning system (DLS). The solution that has been suggested makes use of AlexNet in conjunction with the MATLAB software and a dataset image including 1030 malignant and 868 Benign. When applied to the dataset, the proposed model achieved the following results: 98.3 % sensitivity, 98.2 % specificity, 98.2 %accuracy, 98.7 % sub-curve area (AUC). The model's performance was similar to that of doctors' diagnoses when measured across a total of 1898 images. In the not-too-distant future, as additional data is given to the model, it will grow more accurate and precise, ultimately resulting in the maximum potential detection rate.

Keywords: Detecting liver cancer, liver cancer, learning system (DLS), MRI diagnosis

Introduction:

liver Anatomy:

The liver is located in the upper right-hand portion of the abdominal cavity, beneath the diaphragm, and on top of the stomach, right kidney, and intestines. Shaped like a cone, the liver is a dark reddish-brown organ that weighs about 3 pounds. The liver holds about one pint (13%) of the body's blood supply at any given moment. The liver consists of 2 main lobes. Both are made up of 8 segments that consist of 1,000 lobules (small lobes). These lobules are connected to small ducts (tubes) that connect with larger ducts to form the common hepatic duct. The common hepatic duct transports the bile made by the liver cells to the gallbladder and duodenum (the first part of the small intestine) via the common bile duct.(Eliassaf,2009)

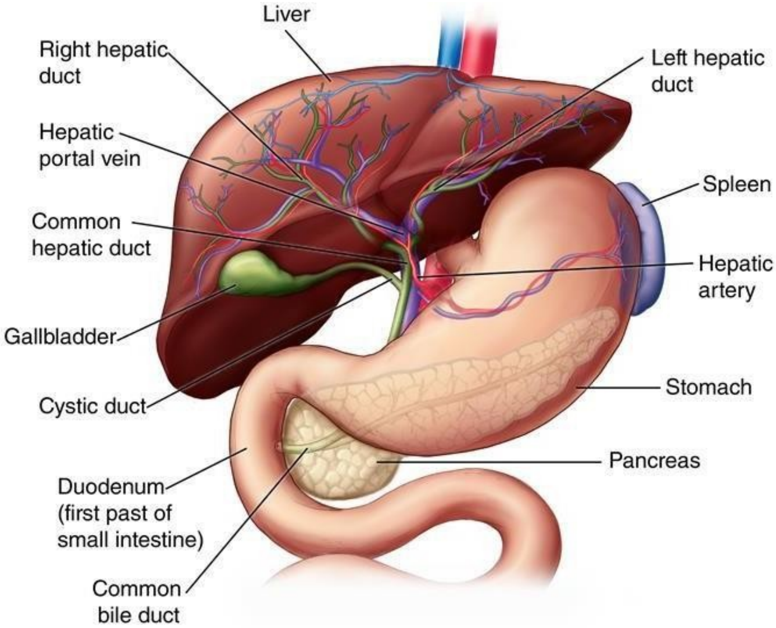

Figure 1: The liver of the human body.

Physiology:

The liver controls the majority of chemical levels in the blood and excretes bile. This aids in the removal of waste materials from the liver. The liver filters all of the blood that leaves the stomach and intestines. The liver processes blood, breaking down, balancing, and creating nutrients, as well as metabolizing medications into forms that are easier to use or harmless for the rest of the body. The liver is responsible for more than 500 important activities.

The flowing are some of the more well-known functions. Production of bile, which helps carry away waste and break down fats in the small intestine during digestion.(Moritz,2007)

- Production of certain proteins for blood plasma.
- Production of cholesterol and special proteins to help carry fats through the body.
- Conversion of excess glucose into glycogen for storage (glycogen can later be convertedback to glucose for energy) and to balance and make glucose as needed.

- Regulation of blood levels of amino acids, which form the building blocks of proteins.
- Processing of hemoglobin for use of its iron content (the liver stores iron).
- Conversion of poisonous ammonia to urea (urea is an end product of protein metabolismand is excreted in the urine).
- Clearing the blood of drugs and other poisonous substances
- Regulating blood clotting.
- Resisting infections by making immune factors and removing bacteria from the bloodstream.
- Clearance of bilirubin, also from red blood cells. If there is an accumulation of bilirubin,the skin and eyes turn yellow.

By-products of the liver's breakdown of toxic chemicals are expelled in the bile or blood. Bile by-products pass through the intestine and exit the body as feces. The kidneys filter away bloodby-products, which then pass through the body as urine.

Cancer of the liver:

The liver can be affected by primary liver cancer, which arises in the liver, or by cancer that forms in other parts of the body and then spreads to the liver. Most liver cancer is secondary or metastatic, meaning it started elsewhere in the body. Primary liver cancer, which starts in the liver, accounts for about 2% of cancers in the U.S., but up to half of all cancers in some undeveloped countries. This is mainly due to the prevalence of hepatitis, caused by contagious viruses that predispose a person to liver cancer. In the U.S., primary liver cancer strikes twice as many men as women, at an average age of 67. Because the liver is made up of a variety of cell types, it can develop a variety of tumors. Some are benign (noncancerous), while others are cancerous and have the potential to spread to other parts of the body (metastasize). Different causes and treatments are used for these tumors. The prognosis for your health or recovery is determined by the sort of tumor you have. (Li.2021)

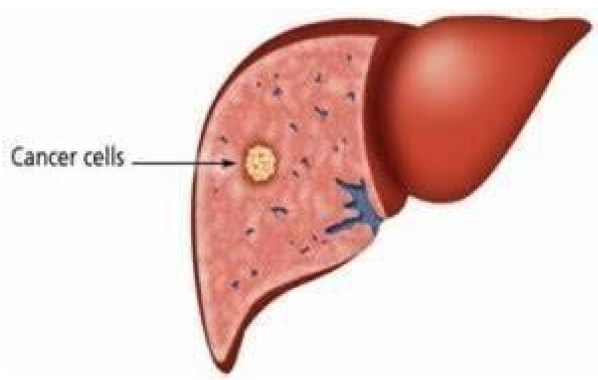

Figure 2: cancer cell in the liver

Hepatocellular carcinoma (HCC)

Hepatocellular carcinoma (HCC) is a type of cancer that begins in the liver. It's not the same as "secondary" liver malignancies, which have moved from other organs to the liver. It can occasionally be cured with surgery or a transplant if discovered early. Although it cannot be cured in more advanced cases, treatment and support can help you live longer and better.(Trevisani.2010)

Cholangiocarcinoma:

These are really cancers of the bile duct.

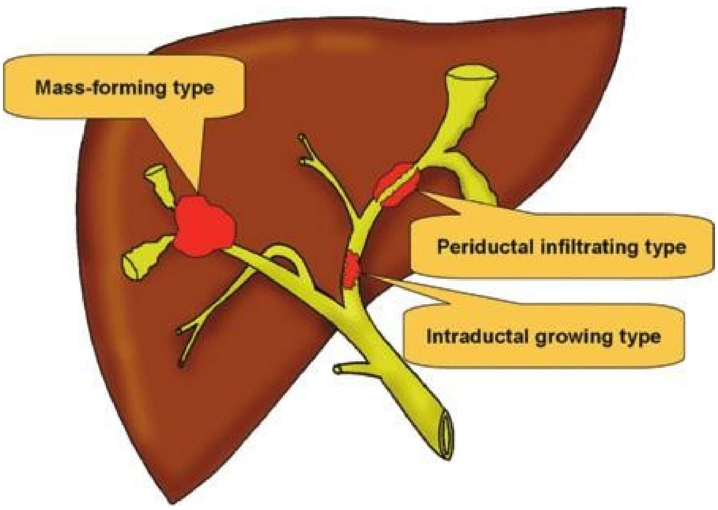

Figure 3: Cholangiocarcinoma

Deep learning:

Deep learning can be considered as a subset of machine learning. It is a field that is focused on computer algorithms learning and developing on its own. Deep learning uses artificial neural networks, which are supposed to mimic how humans think and learn, as opposed to machine learning, which uses simpler principles. Up until recently, the complexity of neural networks was constrained by computational capacity. Larger, more powerful neural networks are now possible thanks to advances in Big Data analytics, allowing computers to monitor, learn, and react to complicated events faster than people. Image categorization, language translation, and speech recognition have all benefited from deep learning. It can tackle any pattern recognition challenge without the assistance of a human.(Wani,et al 2020)
Deep learning is powered by artificial neural networks with several layers. Deep Neural Networks (DNNs) network with multiple layers that can execute complicated operations like representation and abstraction to understand images, sound, and text. Deep learning, the fastest-growing field in machine learning, is a really disruptive digital technology that is being

employed by an increasing number of businesses to develop new business models.(Lucas,et al 2018)

How does work deep learning:

Neural networks are layers of nodes, much like the human brain is made up of neurons. Individual layer nodes are linked to nodes in neighboring layers. The number of layers in the network indicates that it is deeper. In the human brain, a single neuron gets thousands of impulses from other neurons. Signals move between nodes in an artificial neural network and give weights to them. A node with a higher weight will have a greater impact on the nodes below it. The weighted inputs are compiled in the last layer to produce an output. Because deep learning systems process a vast quantity of data and perform multiple difficult mathematical calculations, they demand strong hardware. Even with such advanced hardware, however, deep learning training computations can take weeks. (Bell, J. 2022)

To deliver correct results, deep learning algorithms require a significant amount of data; as a result, information is fed as big data sets. Artificial neural networks may classify data using the answers to a series of binary yes or false questions using highly complicated mathematical calculations while processing the data. A facial recognition computer, for example, learns to identify and recognize faces' borders and lines, then more significant aspects of the faces, and finally overall representations of faces. The program learns and improves with time, increasing the likelihood of the right answers. The facial recognition program will correctly identify facesover time in this situation.(Saxe,et al 2021)
Example to know how deep learning work: Let's imagine you want a neural network to distinguish photographs with a dog in them. For example, not all dogs have the same appearance. Furthermore, photographs depict dogs from various perspectives and with diverse levels of light and shadow. As a result, a training set of photos must be created, which includes many examples of dog faces that anyone would describe as "dog," as well as photographs of items that aren't dogs, labeled (as one might think) "not a dog." The visuals are turned into data by the neural network. These data flow through the network, with different nodes assigning varying weights to different pieces. The last output layer brings together seemingly disparate pieces of information – furry, four-legged, etc. – to produce the result: dog. The neural network's response will now be compared to the label created by a person.(Hinton,et al.2015) The output is confirmed if there is a match. If this is not the case, the neural network records the error and adjusts the weightings accordingly. The neural network attempts to improve its dog-recognition abilities by tweaking its weights frequently. This type of training is known as supervised learning, and it takes place even when the neural networks aren't instructed on what "makes" a dog. They must learn on their own and discover patterns in data over time.

Types of deep neural networks (DNNs):
Multilayer Perceptrons (MLPs):

A feed forward artificial neural network called a multilayer perceptron (MLP) is a type of feed forward artificial neural network. MLPs are the simplest deep neural networks, consisting of a succession of completely linked layers. MLP machine learning approaches can now be utilized to get around the need for a lot of computational power that recent deep learning systems require. Each successive layer is made up of a collection of nonlinear functions that are the weighted sum of all the previous layer's outputs (completely linked).(Gandomi,et al.2013)

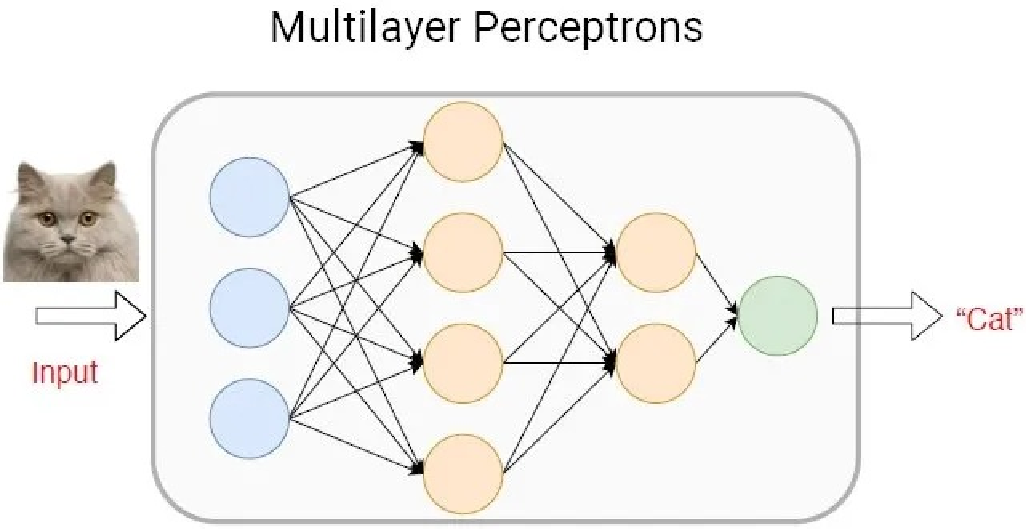

Figure 4: Multilayer Perceptrons (MLPs)

Recurrent neural network (RNN):

Another type of artificial neural network that uses sequential data feeding is the recurrent neural network (RNN). RNNs were created to solve the sequential input data time-series problem. RNN's input is made up of the current input and prior samples. As a result, the node connections create a directed graph that follows a temporal sequence. Furthermore, each neuron in an RNN has an internal memory that stores the information from previous samples' computations. Each successive layer in an RNN is made up of nonlinear functions of weighted sums of outputs and the preceding state. As a result, the basic unit of RNN is termed "cell," and each cell is made up of layers and a succession of cells that allow recurrent neural network models to be processed sequentially.(Wang,et al.2016)

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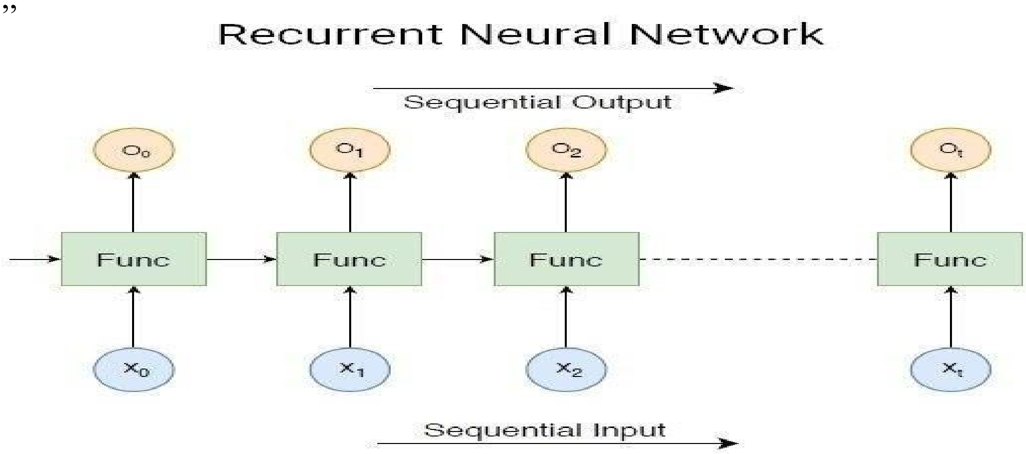


Figure 5: Recurrent neural network (RNN)

Convolutional Neural Network (CNN):

Convolutional Neural Networks (CNNs) are Artificial Intelligence systems that use multi-layer neural networks to learn relevant information from images and perform tasks such as object classification, detection, and segmentation.(Vakalopoulou,et al.2019)
CNNs have an advantage over other classification algorithms (PLM, RNN, Random-Forest, and others) in that they learn the best features to represent the objects in the images and have a high generalization capacity, allowing them to accurately classify new examples with only a few examples in the training set.

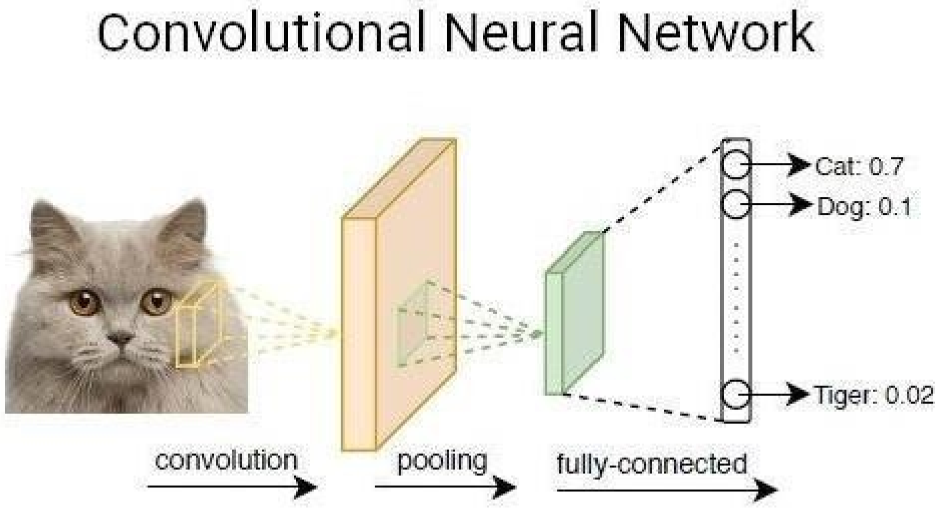


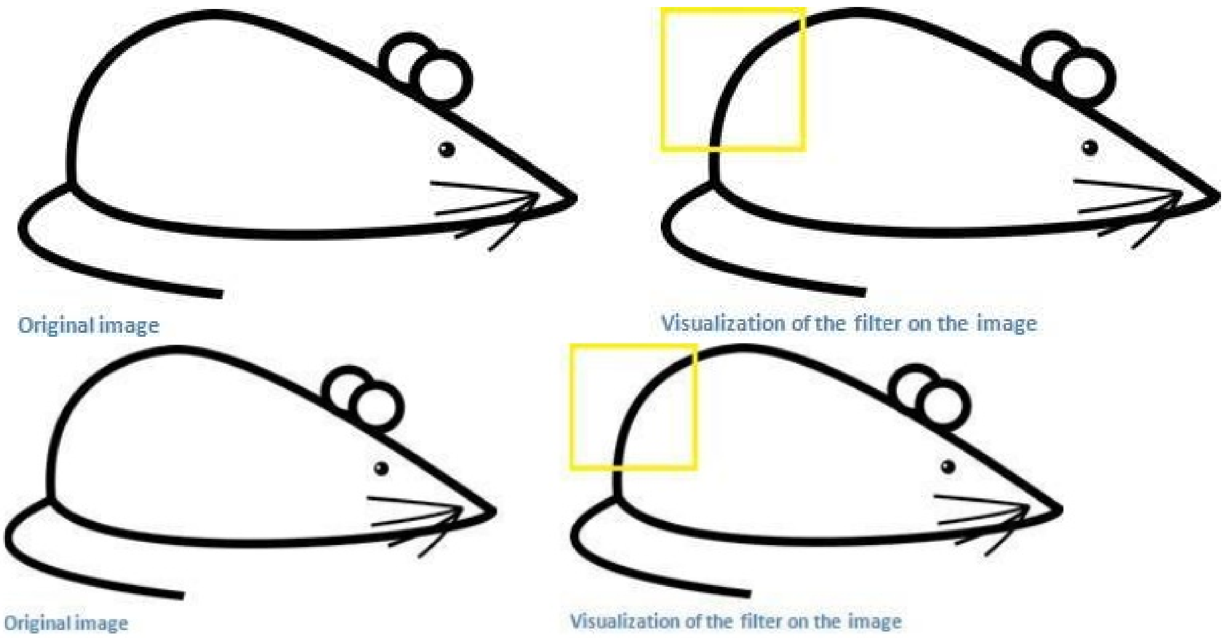
Figure 6: Convolutional Neural Network (CNN)

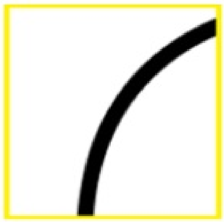
1) Convolutional layer

The convolutional layer is the most important component of a CNN because it is where the majority of the computation takes place. It requires input data, a filter, and a feature map, among other things. Let's pretend the input is a color image, which is made up of a 3D matrix of pixels. This means the input will have three dimensions: height, width, and depth, which match the RGB color space of a picture. A feature detector, also known as a kernel (filter), will traverse the image's receptive fields, checking for the presence of the feature.

A convolutional layer is composed of a set of filters, also called kernels that slide over the input data. Each kernel has a width, a height, and width *height weights. Utilized to extract features from the input data.(Li,et al 2021). The ReLU (Rectified Linear Units) layer, is an activation most lay linked after a convolutional layer to generate non-linearity in the network. The ReLu helps the network to learn harder decision functions and reduce overfitting. The ReLu applies the function y = max(x;0) .(Severyn,et al.2015).

In the training step, the weights in the kernel start with random values and will be learned based on the training set. The convolution technique yields huge numbers when the filter slides over the image and finds a match (activating the filter to that characteristic).(Alzubaidi,et al.2021)





Visualization of the receptive field

0	0	0	0	0	0	30
0	0	0	0	50	50	50
0	0	0	20	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0

Pixel representation of the receptive field

*

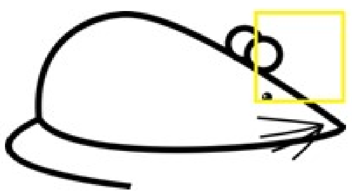
0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter

Multiplication and Summation = (50*30)+(50*30)+(50*30)+(20*30)+(50*30) = 6600 (A large number!)

Figure 7: function of Convolutional layer

But, When the filter slides over the image and finds no match, the filter does not activate.



Visualization of the filter on the image

0	0	0	0	0	0	0
0	40	0	0	0	0	0
40	0	40	0	0	0	0
40	20	0	0	0	0	0
0	50	0	0	0	0	0
0	0	50	0	0	0	0
25	25	0	50	0	0	0

Pixel representation of receptive field

*

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter

Multiplication and Summation = 0

Figure 8:function of Convolutional layer

1.Relu Layer

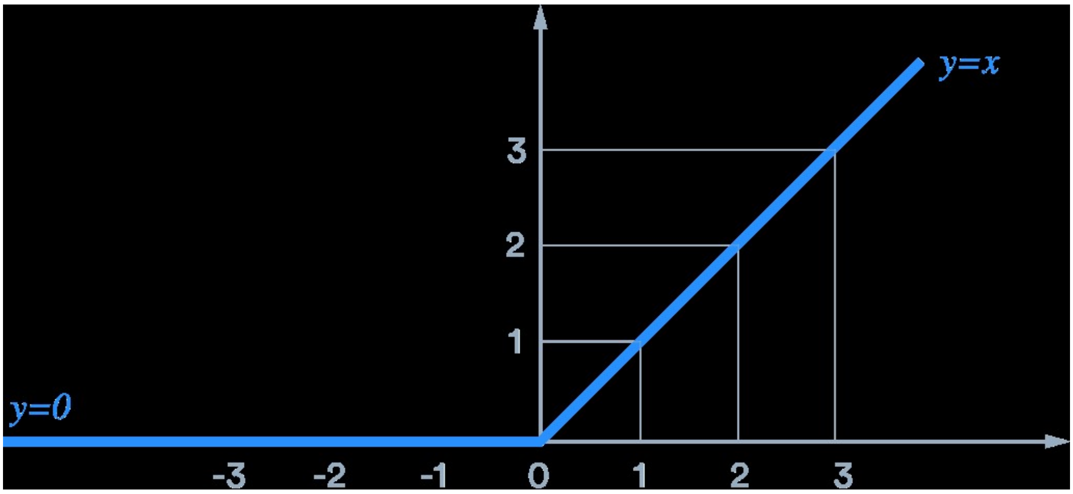


Figure 9 function of Relu layer

2) Pooling layer

Downsampling, also known as pooling layers, is a dimensionality reduction technique that reduces the number of factors in the input. The pooling process sweeps a filter across the entire input, similar to the convolutional layer, however, this filter does not have any weights. Instead, the kernel uses an aggregation function to populate the output array from the values in the receptive field.(Jie,et al.2017) There are two main types of pooling:

- Max pooling: As the filter moves across the input, it selects the pixel with the maximum value to send to the output array. As an aside, this approach tends to be used more oftencompared to average pooling. (Graham, B. (2014).)
- Average pooling: As the filter moves across the input, it calculates the average value within the receptive field to send to the output array.(Hijazi,et al 2015)

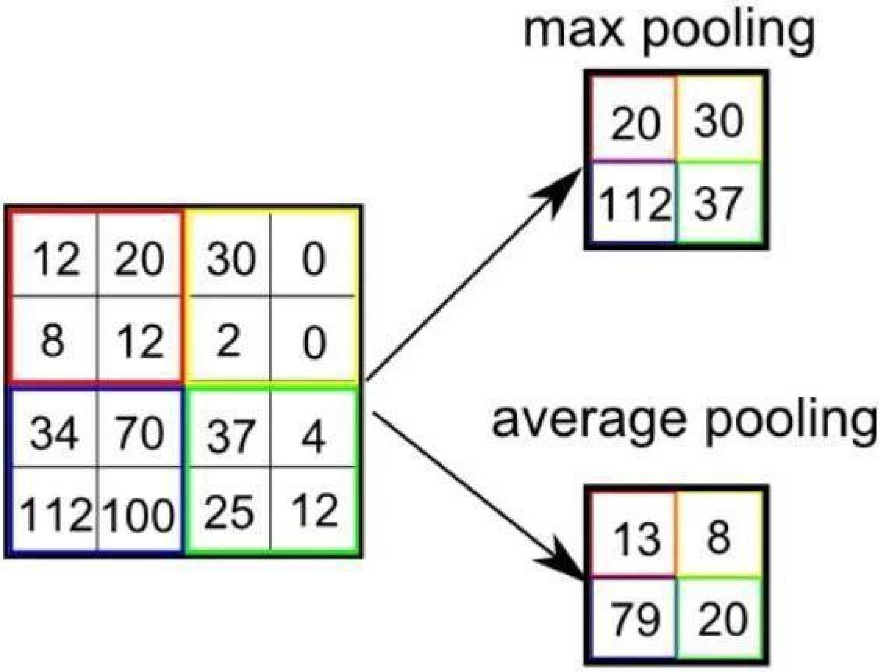


Figure 10 type of pooling

3) Fully Connected layer

The full-connected layer's name is self-explanatory. In partially linked layers, the pixel values of the input image are not directly connected to the output layer. Each node in the output layer, on the other hand, connects directly to a node in the previous layer in the fully-connected layer. This layer performs classification tasks based on the features retrieved by the previous layers and their various filters. While convolutional and pooling layers typically utilize ReLu functions to categorize inputs, FC layers typically use a softmax activation function to produce a probability from 0 to 1.(Nakahara,et al.2017)

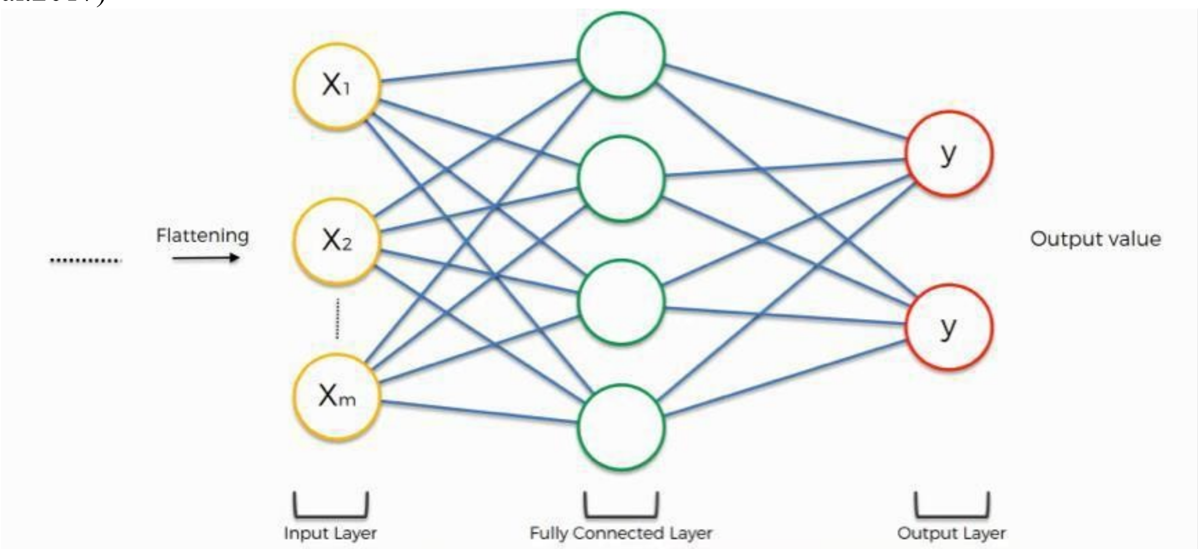


Figure 11 Fully Connected layer

Aim and objective

- Our aim of this study is to develop and test a reliable diagnostic tool, using deep learningtechnology to detect liver cancer from MRI images .
- This tool would accelerate the diagnosis and referral of patients, improving clinical outcomes.
- We believe with more data we can make the proposed model even more accurate.
- Releasing the deep learning model as open source would facilitate the use of the tool bothnow and in any future pandemics, where a similar algorithm could be used.

The structure of the project contain five-chapter

- Chapter 2: In this chapter we will show some of Related to our project to do it.
- Chapter 3: In this chapter talking about methods of project and specification of eachmethod.
- Chapter 4: In this chapter talking about the results of project and discussion.
- Chapter 5: In this chapter talking about the conclusion of the project.

Literature Review:
Methods for liver cancer detection

Laparoscopy:

A laparoscopy may be performed to assess damage to your liver and bile ducts and also to look for tumors in the abdominal cavity. In this procedure, a tiny camera (endoscope) with a light on the end of a flexible fiber-optic tube is inserted into your side through a small cut in your skin (‘keyhole’) to take pictures of your liver. If needed, a biopsy of your liver can be taken at the same time. A laparoscopy is performed under a general anesthetic so you might need to stay in the hospital overnight.(Goossens,et al.2017)
Liver biopsy: usually a diagnosis can be made using imaging but occasionally a biopsy may be required. During a liver biopsy, a tiny piece of the liver is taken for study. Liver biopsies are often needed in trial patients whose tissue needs to be studied and in patients who are to be considered for sorafenib, the drug used to treat primary liver cancer.(Rockey,et al.2009)

Blood test:

Tumor indicators such as alpha-fetoprotein (AFP) are secreted into the bloodstream by organs, tissues, and tumor cells in the body. An elevated AFP level in the blood could be a symptom of liver cancer. Cirrhosis and hepatitis, as well as other malignancies and non-cancerous diseases, can raise AFP levels. Even when there is liver cancer, the AFP level can be normal. (Malati, T.2007) Liver function tests are blood tests that evaluate how many particular compounds are released into the bloodstream by the liver. A higher-than- normal concentration of a chemical can indicate the presence of liver cancer.(Wolf, P. 1999)

Imaging technique:

Ultrasound:

Is a painless test that sends sound waves into the body. The echoes are picked up and used to build a picture of the condition of the liver, bile ducts, and gallbladder. If the ultrasound highlights any areas of tissue that are concerning, you should be referred to a specialist liver unit for a CT or MRI scan. You should be seen by a specialist within two weeks.(Aubry,et al.2013)

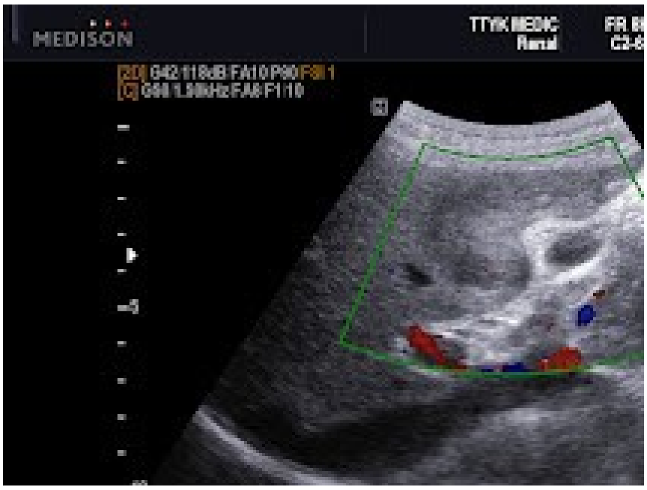


Figure 12 ultrasound scan

Computed Tomography (CT) scan:
His method involves taking a number of detailed photographs of places inside the body, such as the belly, from various angles using a computer coupled with x-ray equipment. To make the organs or tissues show up more clearly, a dye may be injected into a vein or ingested. Computed tomography, computerized tomography, and computerized axial tomography are all terms used to describe this operation. To gain the finest picture of aberrant spots in the liver, images can be taken three times after the dye is administered. (Mattoon, 2006). This is referred to as triple-phase CT. Using an x-ray scanner that scans the body in a spiral route, a spiral or helical CT scan creates a sequence of incredibly detailed photographs of locations inside the body. (Ibrahim, 2016)

Figure 13 CT scan

2.1.3Magnetic Resonance Imaging (MRI) scan:

Magnetic fields, rather than x-rays, are used to create detailed images of the body. A magnetic resonance imaging (MRI) scan can be used to determine the tumor's size. Before the scan, a specific dye called a contrast medium is administered to obtain a crisper image. This dye can be injected into a patient's vein or swallowed as a drink.(Nayshtetik,et al.2016)

Although MRI is frequently regarded as the most sensitive and specific approach for examining the liver, with the recent advancements in multi- detector CT technology, this is definitely arguable. Despite this, MRI has a better lesion/liver contrast than CT, and the flexibility and variety of pulse sequences available in MRI provide a substantial advantage over CT.(Koreanjournal of radiology.2017)

An MRI can assist a doctor diagnose a disease or injury, as well as track your treatment response. MRIs can be used to examine many parts of the body. It's very useful for looking atsoft tissues and the nervous system. Damage to blood vessels, including an aneurysm, can beshown by an MRI of the brain and spinal cord (a bulging or weakened blood vessel in the brain).(Weinstein,et al,2010)

Figure 14 MRI image with tumor

Related work:

Medical imaging plays a vital role in detecting body organ abnormalities. This section analyses and reviews current developments employing machine and deep learning techniques to detectliver cancer using Magnetic Resonance Imaging (MRI) scans.

Zhen, et al 2020 designed a deep learning system (DLS) using convolutional neural networks (CNNs) to classify liver cancers based on enhanced MR images, unenhanced MR images, clinical data including text and laboratory test results, and MR images. They trained CNNs to get binary classifiers using data from 1,210 patients achieved an AUC of 0.946, and 91.9 % accuracy.

Jansen et al., 2019 extracted features from the contrast curve, gray level histogram, and gray level co-occurrence matrix texture from the DCE-MR and T2-weighted images. A primary tumor that is known to exist and risk factors like cirrhosis and steatosis were also employed as features. A set of fifty features with the highest ANOVA Fscore was given to a classifier that uses extremely random trees. The leave-one-out principle and receiver operating characteristic (ROC) curve analysis were used to evaluate the classifier. The classification accuracy for the five main forms of localized liver lesions is 0.77 overall.

(Hamm et al., 2019) designed three convolutional layers with associated rectified linear units, two maximum pooling layers, and two fully connected layers ultimately make up a custom CNN created by repeatedly refining the network architecture and training cases. They used 494 hepatic lesions from six categories with typical imaging features. For training, an Adam optimizer was employed. Cross-validation using Monte Carlo was used. The DLS achieved 92% accuracy, 92% sensitivity , and 98% specificity.

Oyama et al., 2019 analyzed T1-weighted magnetic resonance (MR) images using two radiomics methodologies with machine learning models—texture analysis and topological data analysis utilizing persistent homology—then they assessed the accuracy for classifying hepatic cancers. Their study evaluated 150 hepatic tumors using non-contrast-enhanced three- dimensional (3D) T1-weighted images. In addition to persistence images of three sorts (degree 0, degree 1, and degree 2) being obtained for each lesion from the 3D MR imaging data, texture features were derived for categorization. By using texture analysis, they were able to achieve an accuracy of 92%, with degree 1 persistence images yielding the highest accuracy of 85 (Naeem et al., 2020) employed texture analysis using a fused dataset of two-dimensional (2D) computed tomography (CT) scans and magnetic resonance imaging (MRI) Based on the hybrid-feature analysis. The acquired dataset received preprocessing by applying Otsu thresholding-based segmentation and the Gabor filters to automatically capture regions of interest (ROIs) and decrease noise. The preprocessed dataset was used to obtain 254 hybrid features—a combination of histogram, wavelet, co-occurrence, and run-length features—for each ROI. Ten optimum hybrid features were chosen using the feature selection technique (probability of error plus average correlation). Using a tenfold cross-validation procedure, we deployed this optimized hybrid-feature dataset to four ML classifiers for classification: the multilayer perceptron (MLP), support vector machine (SVM), random forest (RF), and J48. MLP demonstrated a 95.78% on MRI and a 97.44% on CT overall accuracy.

(Wu et al., 2016)developed an end-to-end deep learning algorithm to distinguish between benign cysts and colorectal cancer liver metastases in CT scans. With a 96% accuracy rate, thisstrategy adheres to the InceptionV3 architecture.

Chapter 3: Methodology

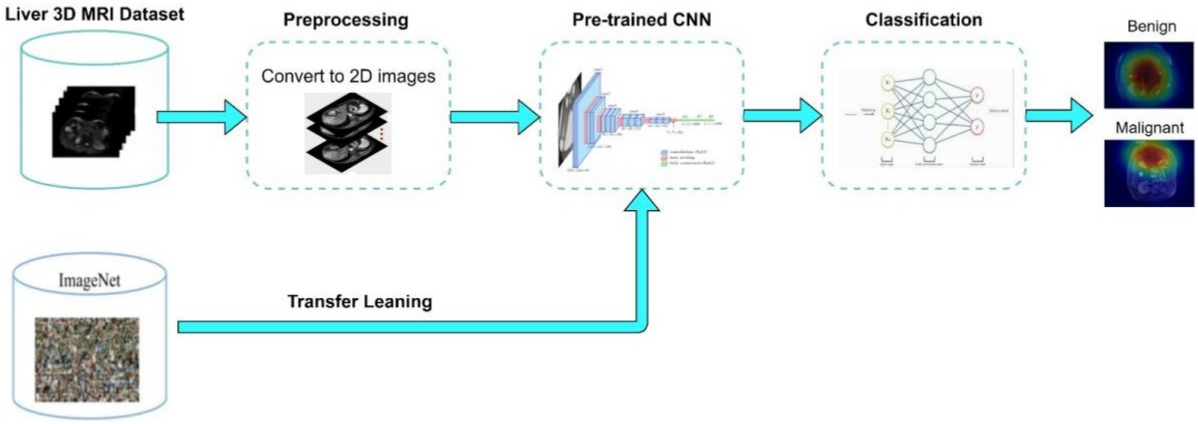


Figure 15: Proposed work flow chart

Dataset

The dataset was used in this project consists of 186 patients with either a malignant (N= 94) or benign (N = 93) primary solid liver tumor. For each patient, a T2-weighted MRI scan is provided. The image is a 3D three-dimensional image, and we dismantled it into two-dimensional images. (Starmans et al. 2021)

AlexNet

AlexNet won top place in the ImageNet image classification competition in 2012. This is very promising for typical machine learning classification algorithms. It demonstrates that the success of CNN in complex models implemented on the GPU allows training to produce resultsin an acceptable time frame, supporting the development of deep learning. For image categorization, AlexnNet employs five convolution layers and three fully linked layers. AlexNet requires 61 million weights and 724 million MACs to categorize the image with a size of 227*227. (multiply-add computation).(Alom,et al.2018)

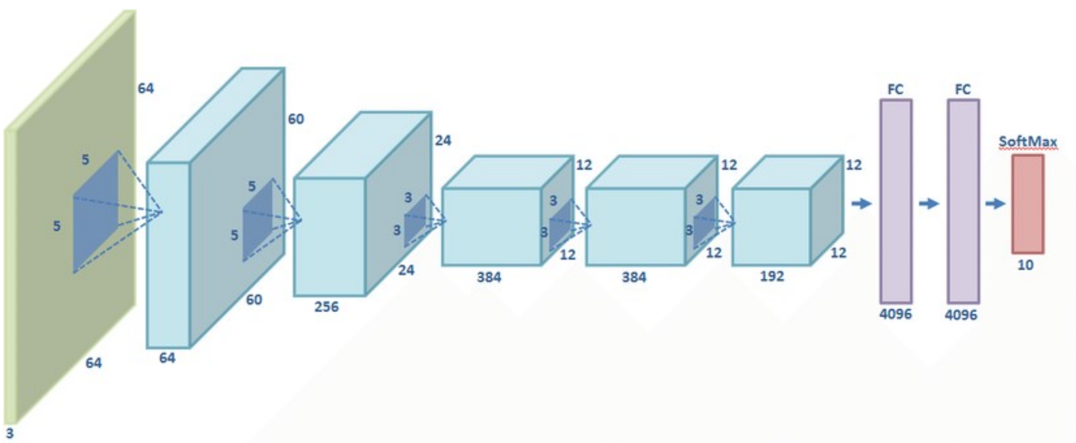


Figure 16 AlexNet

Data Augmentation

Data augmentation is an approach that allows practitioners to greatly expand the variety of data available for training models without collecting new data. Data augmentation techniques like as clipping, padding, and horizontal flipping are extensively employed to avoid overfitting while training large neural networks.(Garcea,et al.2022)

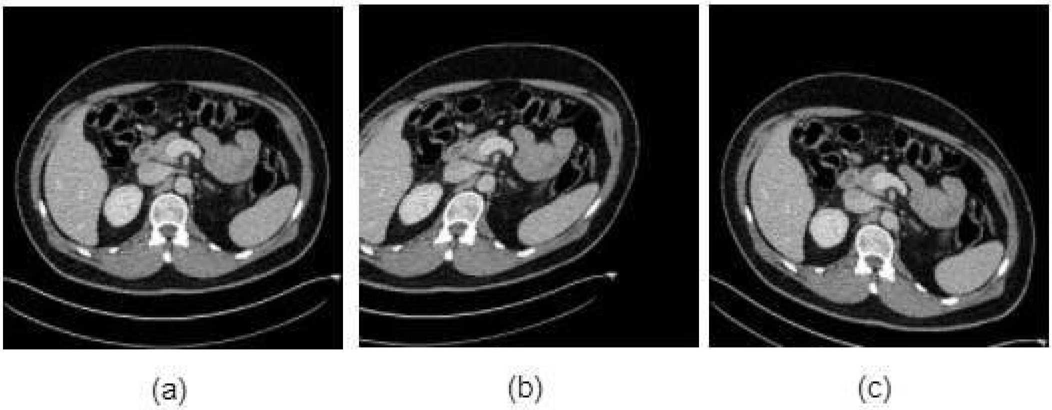


Figure 17 Data Augmentation

Learning Transfer

Transfer learning is a technique in which a model trained on one problem is used in some way on another related problem. Transfer learning is a deep learning technique in which a neural network model is trained on a problem, then additional labeled layers (new classifier) are learned to try to transfer as much knowledge as possible, but the data must be scaled to a specified size for pre-trained size input. The learning process will be faster, more precise, andrequire less training data.(Ghazi,et al.2017)

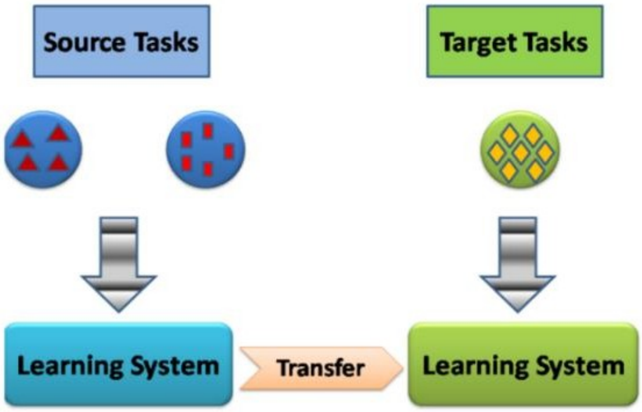


Figure 18 Learning Transfer

Performance Evaluation

Confusion Matrix

A confusion matrix is a tabular representation of your prediction model's performance. Each entry in a confusion matrix represents the number of predictions made by the model in which the classes were properly or erroneously classified.(Chicco,et al.2021)

Confusion Matrix for Binary Classification

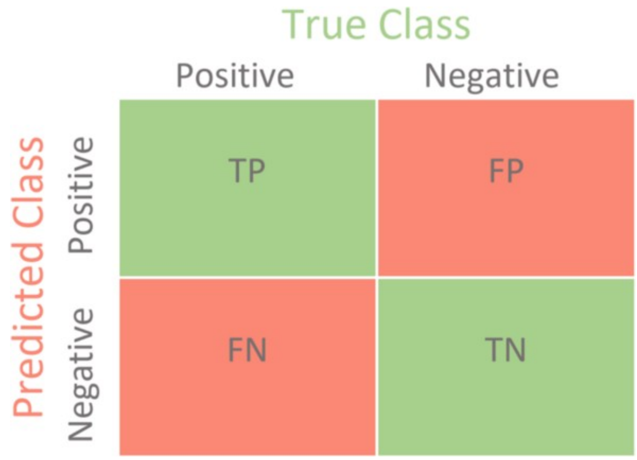


Figure 19 Confusion Matrix

A binary classification problem requires the classification of only two classes, preferably apositive and a negative class. Let's have a look at the Confusion Matrix's metrics now.

- The number of predictions in which the classifier properly predicts the positive classas positive is referred to as the true positive (TP).
- True Negative (TN): The number of times the classifier correctly identifies the negative class as negative.
- False Positive (FP): The number of predictions in which the classifier forecasts thenegative class as positive.
- False Negative (FN): The number of predictions in which the classifier forecasts thepositive class as negative.

From the confusion matrix, below are some of the most prevalent performance measures.

- Accuracy. The number of samples correctly classified out of the total number of samples in the test set.

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

- Recall is the percentage of all positive samples that the classifier accurately identified as positive. True Positive Rate (TPR), Sensitivity, and Probability of Detection are otherterms for it. Use the following formula to compute Recall:

  Recall = $TP/(TP + FN)$.

- Specificity: It informs you what percentage of all negative samples the classifier properly predicts as negative. It is sometimes referred to as the True Negative Rate(TNR). Use the following formula to calculate specificity:

  Specificity = $TN/(TN + FP)$.

- F1-score: A single measure that combines precision and recall. It is the harmonic mean of precision and memory in mathematics. It is possible to compute it as follows:

$$F_1\text{-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} = \frac{2\text{TP}}{2\text{TP} + \text{FP} + \text{FN}}$$

Receiver Operating Characteristic Curve

The ROC curve, also known as the Receiver Operating Characteristics Curve, is a statistic used to analyze the efficacy of a classifier model that compares the True Positive Rate with the False Positive Rate. ROC Curves help determine the precise trade-off between the real positive rate and the false-positive rate in a model that uses various measures of probability thresholds.(Kumar,et al.2011)

The TPR quantifies how frequently the classifier labels data as "positive" when they are not. The FPR quantifies how frequently observations that are actually "negative" are projected as "positive" by the classifier. A perfect classifier's TPR and FPR are 1 and 0, respectively.(Forman.2008)

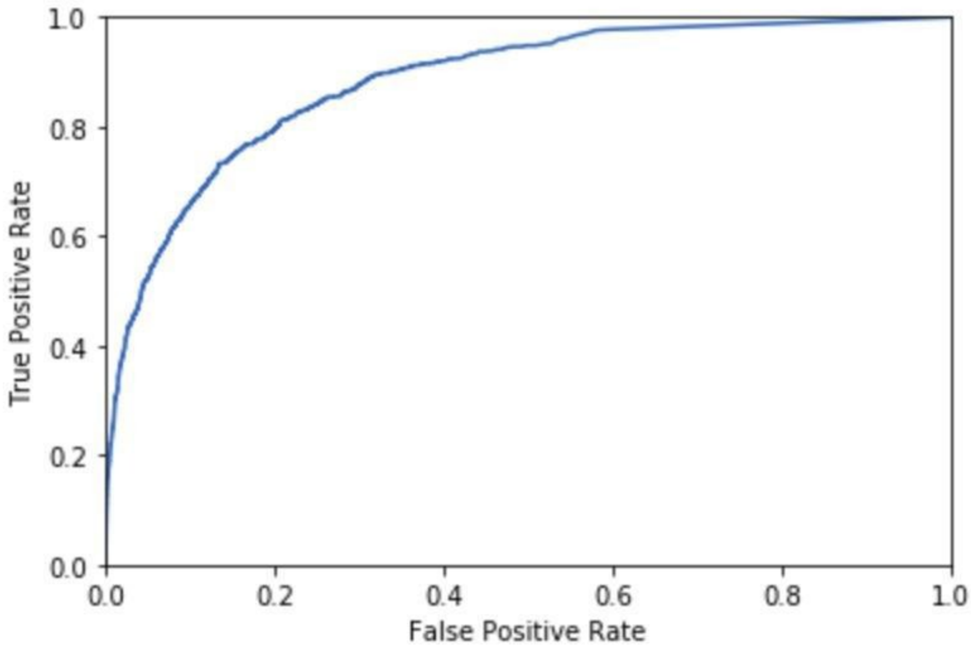


Figure 20 ROC Curve

3.5.3 Area under the ROC Curve (AUC)

One of the most commonly used measures for model evaluation is Area Under Curve (AUC). The AUC measures the complete two-dimensional area beneath the entire ROC curve from (0,0) to (1,1). The AUC allows a classifier to differentiate between classes and is used as a summary of the ROC curve.(Bradley.2009)

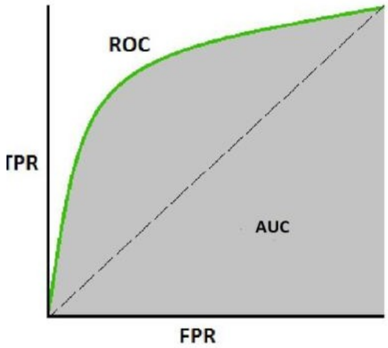


Figure 21 AUC

3.1 Class Activation Map:

Class activation maps make it simple to generate the discriminative picture areas that a CNN employs to identify a specific class in an image. It has numerous convolution layers, the final of which does Global Average Pooling right before the output. The acquired features are supplied into a fully connected neural network layer, which uses the softmax activation function to output the required probability. By projecting the weights back into the feature mapof the preceding convolution layer, the significance of the weights with regard to a category may be determined.(Humphries,et al.2020)

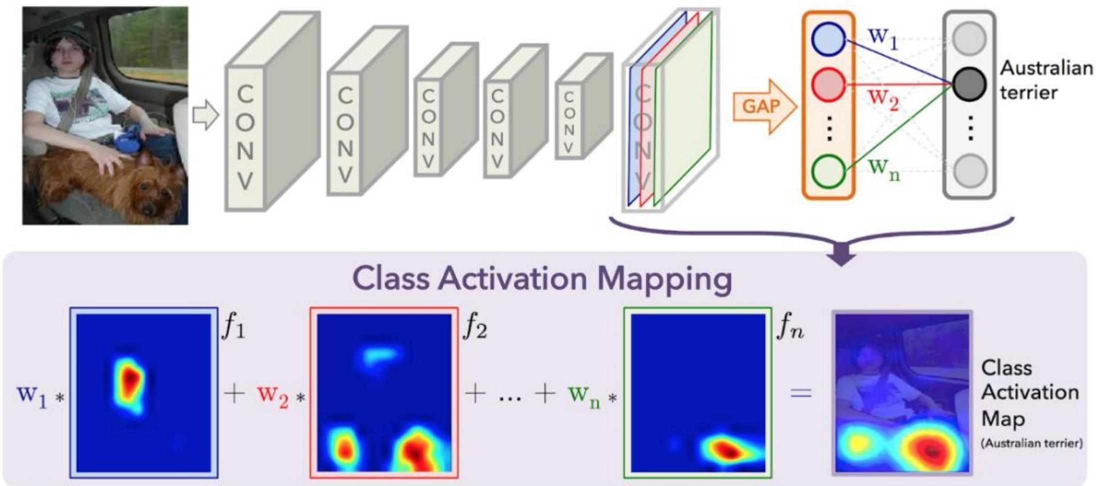


Figure 22 Class Activation Ma

Chapter 4: Results and Discussion:

This project was performed using MATLAB programming language. In this work we used 1898 2D MRI images from 186 3D MRI images .The images divided into 70% training, 20% testing and 10% validation with data augmentation and then fed them into Alex-net pre-trained CNN model. The model was trained via hold out -validation. the validation test is useful for hyperparameter tuning of CNN model . Then Confusion matrix, AUC and Class Activation Map were applied to test the results.

Training

The modified CNN structure was trained on 70% of the available data and tested with 30% ofthe whole data as well. The optimization algorithm exploited to build the training model was root-meansquare propagation (RMSprop) with an initial learning rate of 0.0001. The maximumepochs were 30 with a mini patch size of 32.

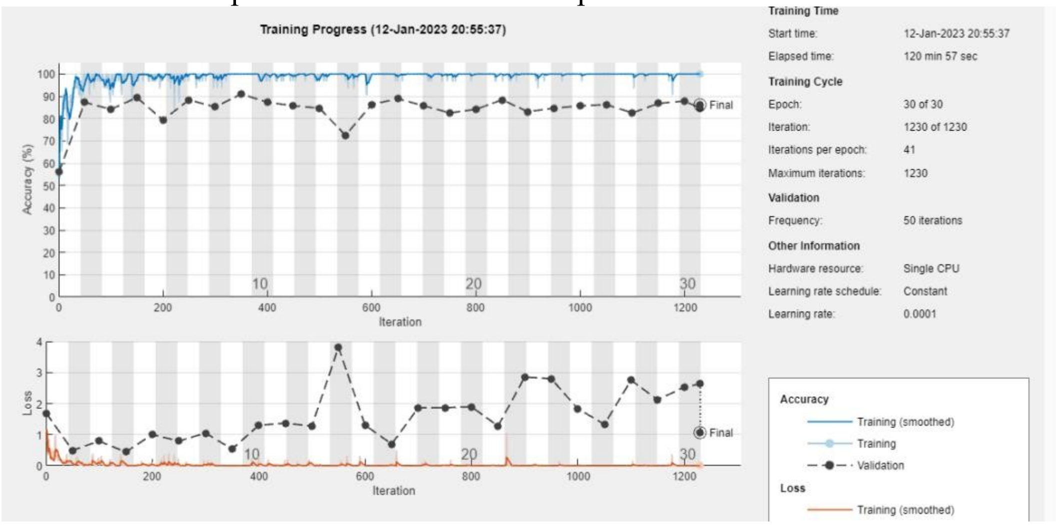


Figure 23 Fold 10 of 10

Testing:

The Figure describes the results using confusion matrix, where the overall accuracy is 98.2.

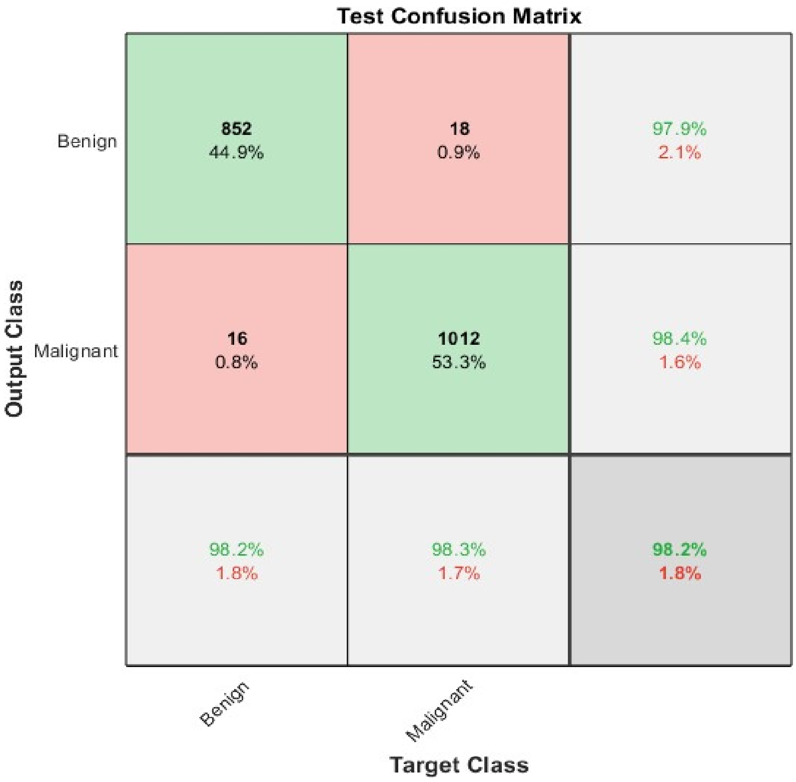


Figure 24 Confusion Matrix Result

Accuracy	98.2 %
Sensitivity	98.3 %
Specificity	98.2 %
F1	98.2 %
AUC	98.7 %

Table 1:Result

Receiver Operating Characteristic Curves (ROC)

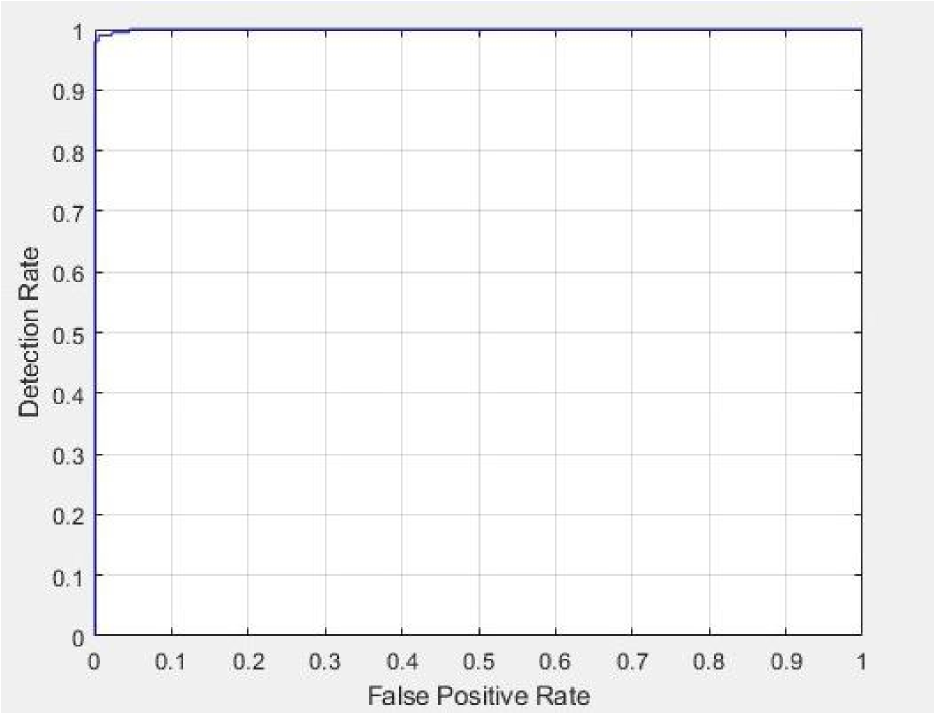


Figure 25 AUC-ROC Result

Classification Activation Map (CAM)

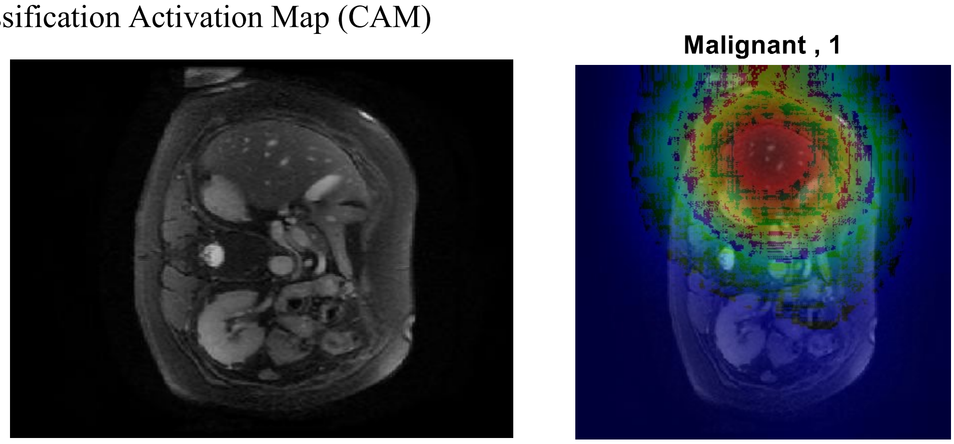


Figure 26 malignant liver cancer

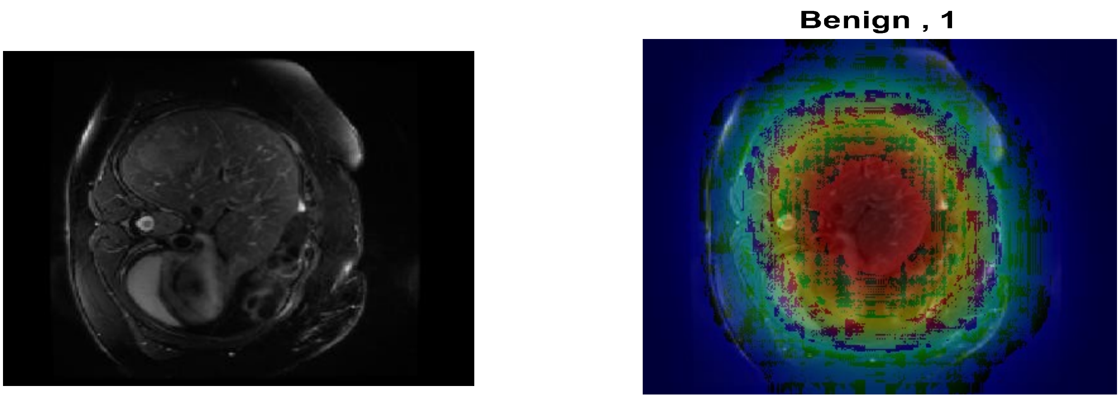


Figure 27 benign tumor

Design Constraints:

There are limitation and lack of MR images for liver cancer and obtaining public dataset has taken a while. Learning how to use the MATLAB software's to extract tumors in liver images features, and developing skills in CNN and deep learning.
Study and educate the basics of CNN was difficult and took a long time and effort understanding how to use CNN packages, start code writing and exploratory data analysis. We would like to make a note that this project was free of charge like; MATLAB software and dataset were free license.
Costs:

There is no any cost since it is modeling project by using MATLAB and public data set .
Engineering Standards:

Table2: Standards-organization

Engineering Standards	**Organization**
MathWorks Advisory Board (MAB) Guidelines	MathWorks with NA-MAAB and JMAAB standards groups
CERT® C Coding Standards	CERT Division of the Software EngineeringInstitute (SEI)
IEC 62304, Medical device software life cycleprocesses	International Electrotechnical Commission

Conclusion and Future Work:

It is challenging to classify liver tumors since, as the liver becomes aberrant, so do the tumor and lesion shapes and textures. As a result, the classification of liver tumors is an ongoing research issue. In the paper, we classified liver anomalies into benign and malignant categories using several classification techniques. Convolutional neural networks (CNNs) were utilized to build a deep learning system from 1898 MRI data (DLS). The suggested approach takes use of AlexNet, MATLAB, a dataset image with 868 benign and 1030 malignant instances of each, and each of these tools in conjunction with the dataset image (Benign, malignant). The proposed model produced the following 98.2% accuracy when used on the dataset. However, after reviewing the data, it was discovered that there were only a small number of false positives, which can be improved by false positive filters and training the model on a bigger dataset.

This model will assist doctors in quickly diagnosing through computer-assisted analysis within seconds. We think that this model will be employed and that it is the best and ideal way to detect and identify the type of tumor that is present in the liver through training. If it is widely used and embraced, it will advance medical research and safe more life's.

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