Liver Segmentation on CT Images for Tumor Detection Using Hybrid Modelling of U-Net, Inceptionv3 and ResNet18

MSc Research Project
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Sandra Pereppadan Ignatious
Student ID: x21195463

School of Computing
National College of Ireland

Supervisor: Dr Ahmed Makki

National College of Ireland

MSc Project Submission Sheet

School of Computing

Student Name:	Sandra Pereppadan Ignatious
Student ID:	x21195463
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Liver Segmentation on CT Images for Tumor Detection Using Hybrid Modelling of U-Net, Inceptionv3 and ResNet18

Sandra Pereppadan Ignatious
x21195463

Abstract

The accurate Diagnosis of disease is highly important in terms of patient treatment. Now a days the tumors like brain tumors, liver tumors etc. are getting higher, where an early and accurate detection will help the patients in treatment. Hence the Deep learning methods can be applied to this scenario where an accurate liver segmentation and tumor detection can be done. My project proposes the solution where a hybrid modelling is being done for the liver tumor detection with U-net, Inceptionv3 and Residual Neural Network (ResNet18). The Research Institute Against Digestive Cancer (IRCAD) dataset contains images of 20 different patients including both genders with 75%of them having tumor. The data is hence used to apply the deep learning methods to apply the segmentation. The hybrid modelling has been applied to the data, where U-Net is the backbone model. While application of U-Net + Inceptionv3 and U-Net + ResNet18, U-Net+ResNet18 performs the best. The project is applied the grey wolf optimiser (GSO) and particle swarm optimiser (PSO) in the preprocessing for the selected model of ResNet18 where the grey wolf optimiser performed the best with average accuracy of 99% and it also have F1 score of 0.98 which also shows that the model has good performance. Furthermore, the model can be useful for the radiotherapy process for cancer treatment and can be integrated with other medical systems for an automatic treatment procedure.

1 Introduction

The medical sector has become more advanced these days, where new treatment methods, machines are getting introduced. The medical imaging technology is one of the advanced one which plays a crucial role in the health care. Now a days, cancer is becoming a common disease which needs to be identified and treated at the early stages of disease. The liver is one of the complicated tissues in the human body, which is hard to diagnose in terms of the liver tumor. As medical imaging become popular in this sector, many deep learning techniques have shown immense betterment in the segmentation of liver and lesion. The study proposes a novel architecture including a hybrid modelling of U-net and ResNet18 architecture. The computed tomography (CT) scan images from the IRCAD database, has been used here to conduct the research.

This U-Net architecture has encoder and decoder mechanisms connected with a bridge containing 4 decoder and encoder blocks and it also have incredible detailed feature identifying mechanisms, which will capture the small and detailed ones. The U-net method is hence integrated with the inceptionV3, which is high architecture of conventional inception network, and it has 48 layers which trained on large number of datasets. The U-Net also integrates with ResNet18 a deep convolutional neural network conations 18 layers which accepts the single image data and a model trained on the large dataset called imagenet. Finally, the model is also applied with the optimisers, particle swarm and grey wolf optimiser.

1.1 Motivation And Scope of Research

The liver tumor can be mostly a cancerous tumor, hence it very important to detect it in early stage. As now the conventional methods of human involving in diagnosis involve a lot of human effort and it takes the treatment procedure slow. At this point the project is to think about implementing a fast detecting and accurate mechanism for the tumor detection, where the current methods do the job perfectly other than the conventional methods, by using a hybrid novel architecture. The following method can be applied in the other system or applications in the medical sector for the treatment. There are many systems which used for the treatment for liver tumor.

Surgical resection: The liver tumor is needs to be detected properly to conduct the surgical method. The inaccurate lesion detection will take the life of patient and the method can be integrated with this to find the section of tumor.

Thermal ablation and radiation therapy: The thermal ablation is used in patient body after finding the cancerous area and applying microwaves or radio waves to remove the section and our method will be also useful for this.

1.2 Objective of the Project

The research follows certain objectives during the implementation of the project, starting from the literature review as follows:

- After reviewing the litterateur review. Creating a Kaggle virtual space for the project. Inputting data to the variables
- Data pre-processing including, normalisation, bilateral filtering, GSO and PSO application and feature creation.
- Design and implement the model on the data and selecting the best model performs the best in terms of accuracy and other values.
- Finally, the results are being discussed and evaluated based on values and accuracy measures.

1.3 Research Questions

a) Is the U-net + ResNet18 model or U-Net +Inception is better for liver tumor segmentation compared to other models used in the field?

b) Does the Grey wolf optimiser work better with the hybrid ResNet18 model than Particle swarm optimiser?

1.4 Structure of the Report

The research aim is to detect the lesion on the liver, where the section 1 gives a detailed introduction about the project and its details, where the further section explains about the motivation of the research and its scope. The section 1.2 discusses about the objective of the paper. The research question is also being discussed and section 2 talks about the related work. Section 3 follows on the research methodology in detail and section 4 describes the design specifications of the project and the section 5 explains the implementation follows with the section 6 of evaluation of the results and ends with the conclusion and future work of the project.

2 Related Work

2.1 Liver Tumor detection using IRCAD Dataset

The study (Almotairi S., et al., 2020) focus on the idea of the cancer detection in hepatic area and using the SegNet architecture with VGG-16 as the primary encoder with higher max pooling efficiency and high training speed and good accuracy. The research paper conducts a modelling with IRCAD dataset and produces 86% of accuracy in the tumor segmentation. This research has low-rate false positives and intended to use much good deep learning models in future to produce higher results. (H. Seo., et al., 2020), the work proposes U-Net model for the liver segmentation purpose to avoid human diagnosis in the laboratory. The U-net here is added with an additional residual path with deconvolution to avoid the general drawbacks of the architecture.

The proposed project uses the famous dataset LiTS. The model has acquired the volume of error of 21.93% and RVD of 0.49% for the liver tumor segmentation. The modified Unet performed better with the Lits and IRCAD dataset with the dice coefficient of 89% on LiTS and 96% on Ircad dataset. The advantage of the model is that it can applied to any other dataset without having any preprocessing steps in it and it also works fine with the other images like MRI, PET images as it works with the CT images. (H. Jiang., et al., 2019), the paper tells that, even after having multiple number of methods the liver segmentation still remains a task because of the complexity it has among the others and also it related to a risky fieldThe extensively used Ircad and Lits dataset has been used here to detect the tumor and aim to reduce false positive values. The AHCNet model shows accuracy of 94 % on liver and shows accuracy of 62% in tumor detection. The limitation of the model is that it has a lesser accuracy than current works where the work future work is to expand the gpo and applying more preprocessing methods and produce better results.

2.2 Liver tumor segmentation using CNN Methods

The research paper by christ (Christ, P.F., et al., 2016) proposes an idea to do segmentation on the liver and the tumor part of the liver for diagnosis purpose in medical field and for the computer applications in the field. The research authors used CFCN and FCN for the segmentation. The result of the modelling gives 94% accuracy for the liver lesion segmentation with the model CFCN. The paper method is capable enough to work on different images from CT scans and produce better results. The paper hasn't suggested a better improvement in terms of accuracy and future work. The research paper by Chlebus, G., et al., (2018) introduces a method using 2D CNN and object post preprocessing. The model acquires a high amount reduced false positive rate of 85% compared to the normal CNN method. The model achieves similar accuracy compared to humans in terms of segmentation, but the conclusion of the paper cites that, the model still needs a human clinical observation. The model works better with the 2D images and on the larger lesions which seems to be the reason of inter-observer variability. The model future proposal includes 3D images as an input to achieve a higher accuracy with competes the human involvement and includes automatic reporting of the liver lesions. (Ben-Cohen., et al., 2016) The study proposes the method for tumor detection using FCN. The FCN method is being compared with the sparsity-based classification methods and patch-based CNN method. The study is being conducted in small dataset from a medical centre where the model FCN performs better with the true positive value of 0.86 and acquires the false positive as 0.6 on each case. The outcome produced is highly same as a human involvement. The observation shows that FCN combined with other models also performs best and it have a lot of room for improvement in future about the performance by applying serval other methods into it. The research also plans to improve the results by expanding the project with 3D analysis and with larger dataset aim to produce better predictions on the same. E. Trivizakis et al. (2019), in the research a 3-dimensional CNN model is being proposed for tissue classification in the MRI images. The model has 4 convolutional layers with rectified liner unit function and 3*3*3 kernal and fully connected layer and softmax layer. The 3D CNN results show that, it have 83% of accuracy compared with the 2D model where it have 65.2 % accuracy. The advantage of the 3D model is that, it performs without any preprocessing step or no need of adding interested areas, it will operate directly with the 3D data. The results shows that 3D architecture in the liver segmentation have seamless performance compared to others. T. Fan., et al., (2020) , this author talks about the issues of liver tumor detection in the clinical process, while it can be helped with the U-net based model with multi scale fusion which will improve the scenario. A novel scenario of MA Net has been introduced here which will intently help to integrate the local features of the data with the global features in it. The approach was designed to make two blocks PAB and MFAB. The dataset used is MICCAI Lits dataset for the detection purpose. The method provides an accuracy better than another model in this area with the dice value of 0.96+0.03 and also having dice value of detecting tumor with 0.749+0.8. The model MA net perform better with the conventional UNet model.

2.3 Liver Segmentation for tumor detection and other tumor detection related works

Q. Yan et al.(2021) **,** The paper addresses about the segmentation of lover vessels in the field od diagnosis of diseases. To avoid the labour work by humans in the clinic, the deep learning model LVSnet is being used which works with the attention guided concatenation and MSF

blocks. The dataset used is ircad dataset with 40 cases including thin vessels cases as well. The model AGC selects the features for the segmentation and the model MSFF build connections in the blocks linking the vessels fragments. The limitation of the current study is about the accuracy, where it can better in future if better models and datasets are applied.
(S. -T. Tran., et al., 2021) the paper talks about the liver tumor segmentation using U-Net. The paper has finally predicted accuracy of 96.5% and it has used U-Net and U2-Net for the implementation with the use of widely used datasets of medical imaging is Ircad and Lits and its advantage is that it has two datasets with average results compared, but it has to make use of better model to get better accuracy and functionality.
Y. Zhang et al. (2020) study of this paper is based on 2d model of U-net and 3D based CNN model. The study has got a proven accuracy of 84.1% for liver and 96.7% on liver tumor. The advantage of the study is that it has done two approaches for liver segmentation and as well as for tumor segmentation. The study in future is planning to incorporate a Dense Unet architecture which seems to show better accuracy.
(S. Qamar., et al., 2018), the paper deals with the brain tumor segmentation, which also have similar approach of using a 3d hyper dense method of CNN. The dataset used was BraTS 2018 for the study and they got an accuracy of 0.87. The advantage of the project is they are using 3D images for the purpose, which can be used for the next level future diagnosis. L. Balagourouchetty., et al., 2020) , the method used for the study id googlnet, FCnet classifier model and it have produced 97.37% accuracy, with the models. The stu dy has a advantage is that, they have shifted from the conventional methods, and focused on a new one and they got a better value which can improved in future.

3 Research Methodology

The process followed here is KDD, which is known as “knowledge discovery in databases”, This is a common method used in segmentation purpose of medical imaging. The KDD process follows a specific way to achieve this, At first the data is being collected from a source and the data is loaded to specific variable called df , followed with pre-processing steps which can include the methods like null vectorisation, normalisation etc. After this process, the data is applied with several deep learning models and then the training is done on the training data. At the end, training data is compared to with the test data to see the results, followed by statistical evaluation methods. The project have followed this process to my research methodology.

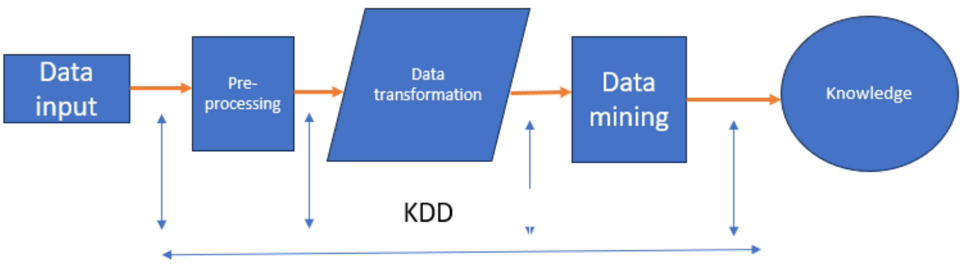

Fig 1: KDD methodology

The study used the deep learning model for the image segmentation for this hybrid modelling is U-Net. The U-Net architecture is a most used method for image classification in medical field. The architecture is used by [Ronneberger, O., et al., (2015)](#) in the paper for biomedical research, where U-net have performed much better than other models for segmentation purposes. The U-net architecture have contracting path and expansive path where the architecture generally has 3*3 convolution layers and 2*2 max pool layers, study is applying U-Net with Inception and U-net with resnet18. The U-Net and ResNet18 worked better in terms of accuracy. Below shows the architecture diagram of U-Net and ResNet18.

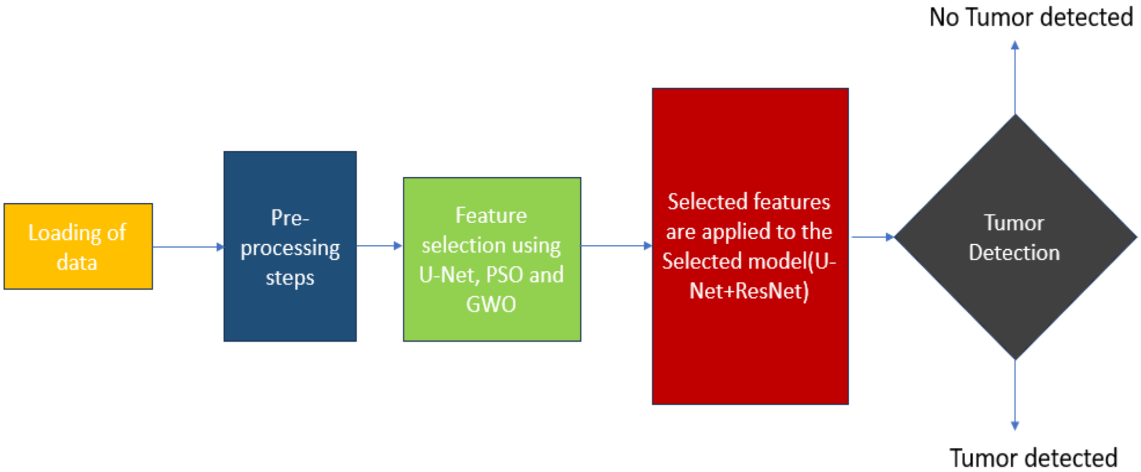

Fig 2: Process flow diagram of project

The above is a diagram which shows the process followed in the project. The data is collected from the IRCAD website, and it is loaded to the variable. The EDA is being performed to check if the data is loaded correctly. The pre-processing steps like normalise matrix formation and vectorisation are being performed on the data. Following process are done with the data later:

First Half of project:

- The feature selection is done by the U-Net and later the Inceptionv3 is applied to the data and a hybrid modelling architecture is being carried out in the process.
- The model ResNet18 is also being applied with the U-Net after the feature selection.
- The results of the comparison have been taken and a best model is selected which proves to be **U-Net+ResNet.**

Second Half of the project:

- The best selected model U-Net+ResNet18 is being applied with the grey wolf optimiser and applied with the particle swarm optimiser to prove which serves better for the selected model to perform well.
- The final model is being selected as **Grey wolf optimiser and U-Net+ResNet18.**

3.1 Data Collection and Loading

The data is collected from IRCA[1]D website, which is a educational institute for cancer and other studies. They published this dataset on their website, and it is a widely used dataset for medical imaging in this field. The dataset name is “3D-IRCADb-01” which contains the images of 20 different patients including 10 women and 10 men mostly having around 75% of liver tumor. The 20 folders having 4 sub folders with the data of liver image, the mask image used for predication and the tumor image as well.

The exploratory data analysis(EDA) has been performed in the dataset listing all the tumors from the different folders, shows that the data has correctly loaded to the environment, and it contains images with the 512*512 pixels. The collected data is mostly free from the noises and other issues as the data is mostly in the pre-processed form. The collected data have around 128 rows with 3 columns in it. The data needs to be in a array to perform the later operations and hence the remaining steps of data preparation needs to be done.

3.2 Data Pre-processing steps

The data pre-processing is the next step performed, where the data is being loaded to the array to give a perfect structure for the data to work in the modelling purpose. The data used in the project are subjected to the preparation to avoid unnecessary noises and issues in the data. The data have undergone several methods following below:

Data Array Initialization:

The data is in pixel format of 512*512 of pydicom image is inserted to an array for getting an efficient manipulation of data. While the data is stored in an array gives a structured format to operate within and for analysis as well. The array storage is mostly compatible with all the machine learning languages and deep learning languages present. By loading the data in array, all the pixels size of images are denoted with a numerical value which makes the use of data in model easier.

Vectorization:

The vectorisation is applied to the array to make the data easier to work in the deep learning models. The array after applying the method will be in an optimised manner to work efficient in a code. The advantage of applying this method is code simplicity and easy to manipulate the data. After these methods of pre-processing data is ready for the feature selection.

Normalization:

The normalize matrix formation is a pre-processing step performed here to get the data in a specific range and value, to get an accurate modelling result and avoid noises. The normalization has benefit of scaling data and attain a numerical stability for the data. The data is printed after the normalization as below:

[1] https://www.ircad.fr/research/data-sets/liver-segmentation-3d-ircadb-01/

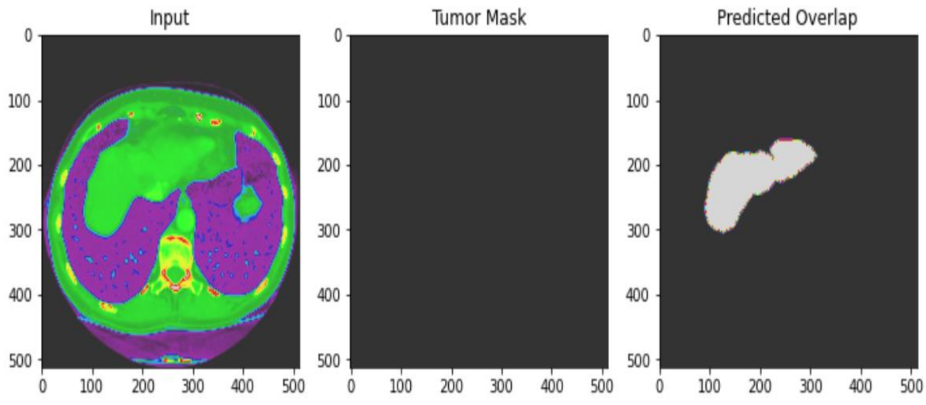

Fig 3: Data after prepration

3.3 Feature Selection

The feature selection in the tumor detection is a complicated one, as the liver is a small organ with lots of specific details. The features selected would be mostly based on the colour, texture and the size of the liver which have tumor. This task needs to do with a better architecture to find the spatial details in the organ and hence this is performed by the inbuilt architecture of U-Net, which have the special capability to go in details and take the relevant features. The U-Net have high capability in segmentation as it will go into the specific details of the image including each intrinsic feature which are hard to notice.

3.3.1 Particle Swarm Optimiser

The particle optimisation works in such a way that the particles are passed through a mutlti-dimensional space to find the best solution for the big issues. Each particle scan be considered as each solution for the problems. When the particle passes through the search area, each of them checks their velocity and finds out which have the best performance, After the velocity has determined, each particle will change their position in the area and fits with a position. By the optimiser, we have reduced the computational power 49.78% and formed a subset of feature selection with 1316125. After the application of the same, the modelling is performed with the best selected model.

3.3.2 Grey Wolf Optimiser

The grey wolf optimisation is a natural based algorithm to optimise the features in the segmentation code. The method is used in the code, where the solutions are considered as wolf, and it also have leaders and they align their position based on the leaders stand. They also find the best feature based on the groups they belong and their positions. Here project used the same and selected the best subset of features with 209555 numbers and the computational power reduced to 20.06. The following code is run with these subsets of features selected.

3.3.3 Adam Optimiser

The project using Adam optimiser in every code to make the solution smoother and easier to manipulate. This is mostly used technique in deep learning and in segmentation purposes. The study used this model for the training phase, where the method balances the models' weights on the basis of loss function and always acquire the balance and generalise the modelling technique.

3.4 Modelling

The hybrid model application has been done here. The U-net is the base model, where we apply the Inceptionv3 on the first half and the training of the model is run for 100 epochs. Inceptionv3 is a convolutional model and The study used 2nd and 4th encoder and decoder of U-Net as it is suitable inceptionv3. The same has been done for the ResNet18 and study used U-Net large convolutional neural network(CNN) model for the iteration, as the segmentation needs large CNN model on picture to load and process the images and segment the liver tumor. The ResNet and U-net combination worked better in the first half. Hence, we have used the two optimisers, Particle swarm optimiser and grey wolf optimiser. The model has again run for the training after the application of optimisers and then the best model was selected based on the testing and accuracy of the model. The total convolution used were 101 and the max pooling layers used were 3 which produced a better result in terms of current segmentation methods.

3.5 Evaluation techniques

Evaluation techniques are used to analyse the quality of the result we have acquired. project used the techniques like Recall, sensitivity, loss value, F1_score etc. The study considered False positive value as a major evaluation technique as the project is related to medical field where none of the data or result obtained should be falsely positive. The F1 score will analyse the performance of the model and Val loss function gives idea about the loss of the values in the detection method. Accuracy was also a metric used for the evaluation. Below table shows detailed use of evaluation techniques.

Evaluation technique	Explanation
Accuracy	It describes how accurate the model is.
Sensitivity	Measure to find out the variations in model
Specificity	Measure to identify the true negative values rate.
F1_Score	It's an evaluation method for finding the accuracy of model

Table 1: evaluation techniques used.

4 Design Specification

The project uses the Advanced U-Net architecture for segmentation purposes with the combination model InceptionV3 and ResNet18. At the end of research, we are taking the Resnet18 for the implementation purpose as it performs better. Below shows that architecture table for the same.

Layer Type	Encoder/Decoder	Output Shape	Kernel/Filter Size	Number of Filters
Input	-	(512, 512, 1)	-	-
Conv2D (x5)	Encoder	(512, 512, 64)	3x3 size	64
Conv2D (x5)	Encoder	(512, 512, 64)	3x3 size	64

Layer Type	Encoder/Decoder	Output Shape	Kernel/Filter Size	Number of Filters
MaxPooling2D	Encoder	(256, 256, 64)	2x2 size	-
Conv2D (x3)	Encoder	(256, 256, 128)	3x3 size	128
Resnet (x18)	Encoder	(256, 256, 128)	3x3 size	128
MaxPooling2D	Encoder	(128, 128, 128)	2x2 size	-
Conv2D (x2)	Encoder	(128, 128, 256)	3x3 size	256
Conv2D (x3)	Encoder	(128, 128, 256)	3x3 size	256
MaxPooling2D	Encoder	(64, 64, 256)	2x2 size	-
Conv2D (x2)	Encoder	(64, 64, 512)	3x3 size	512
Resnet (x18)	Encoder	(64, 64, 512)	3x3 size	512
Resnet (x18)	Encoder	(64, 64, 1024)	1x1, 3x3, 5x5 size	256, 256, 512
Conv2Dtranspose (x 5)	Decoder	(128, 128, 512)	2x2 size	-
Concatenate	Decoder	(128, 128, 1024)	-	-
Conv2D (x5)	Decoder	(128, 128, 512)	3x3 size	512
Conv2D (x5)	Decoder	(128, 128, 512)	3x3 size	512
Conv2Dtranspose (x 5)	Decoder	(256, 256, 256)	2x2 size	-
Concatenate	Decoder	(256, 256, 512)	-	-
Conv2D (x3)	Decoder	(256, 256, 256)	3x3 size	256
Conv2D (x3)	Decoder	(256, 256, 256)	3x3 size	256
Conv2D (x3)	Decoder	(512, 512, 64)	3x3 size	64
Final Output	Decoder	(512, 512, 1)	-	-

Table 2: Architecture diagram

The architecture follows above kernel, convolution layers, max pool layers etc. The architecture operations can be seen in the below diagram. 101 convolution layers are used in total and 3 max pooling layers are also applied in the modelling.

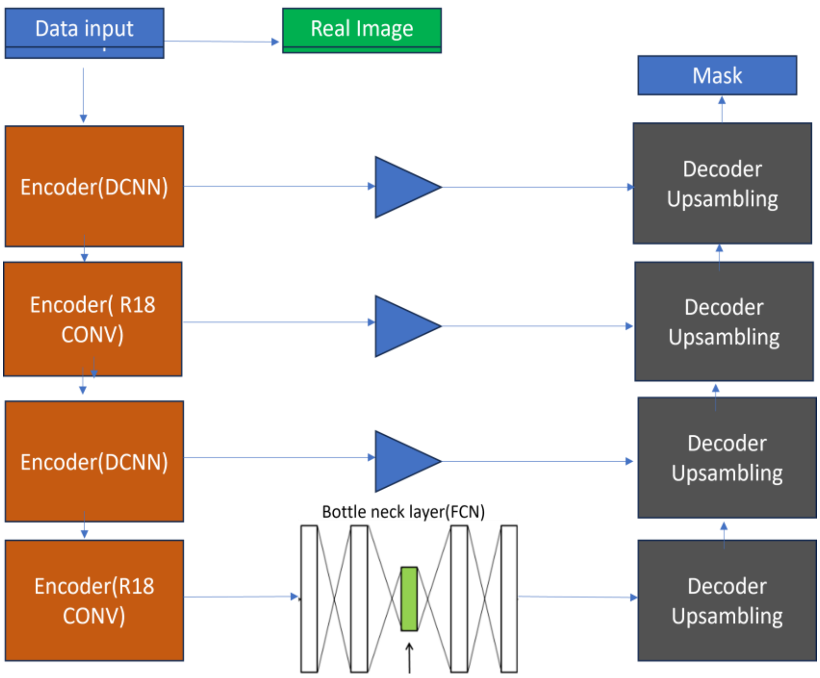

Fig 4: Process of modelling

5 Implementation

The implementation used several software's and technologies for the development and all of them are listed below in the table.

Programming language	Python
IDE	Jupyter notebook with Kaggle GPO
Libraries	Pandas, NumPy, matplotlib, sklearn, TensorFlow, seaborne, pydimcom, pytorch

Table 3: Technology and software details

5.1 Data Exploratory Analysis

The data is taken from iracad website, and it have around 128 columns and rows of data as plotted below. The data is loaded to a variable called Df and it is later converted to the array for easy manipulation and access.

	Image	
0	../input/liver-segmentation/Dataset-1/dataset/3Dircadb1/3Dircadb1/3Dircadb1.1/PATIENT_DICOM/PATIENT_DICOM/image_1	1/dataset/3Dircadb1/3Dircadb1/3Dir
1	../input/liver-segmentation/Dataset-1/dataset/3Dircadb1/3Dircadb1/3Dircadb1.1/PATIENT_DICOM/PATIENT_DICOM/image_60	1/dataset/3Dircadb1/3Dircadb1/3Dirc
2	../input/liver-segmentation/Dataset-1/dataset/3Dircadb1/3Dircadb1/3Dircadb1.1/PATIENT_DICOM/PATIENT_DICOM/image_31	1/dataset/3Dircadb1/3Dircadb1/3Dirc
3	../input/liver-segmentation/Dataset-1/dataset/3Dircadb1/3Dircadb1/3Dircadb1.1/PATIENT_DICOM/PATIENT_DICOM/image_99	1/dataset/3Dircadb1/3Dircadb1/3Dirc
4	../input/liver-segmentation/Dataset-1/dataset/3Dircadb1/3Dircadb1/3Dircadb1.1/PATIENT_DICOM/PATIENT_DICOM/image_96	1/dataset/3Dircadb1/3Dircadb1/3Dirc

Fig 5: Data exploratory analysis

The data is loaded, and the loaded data contain liver as X, mask as Y and y_liver as liver tumor. The below picture shows that taken mask and liver picture of the data.

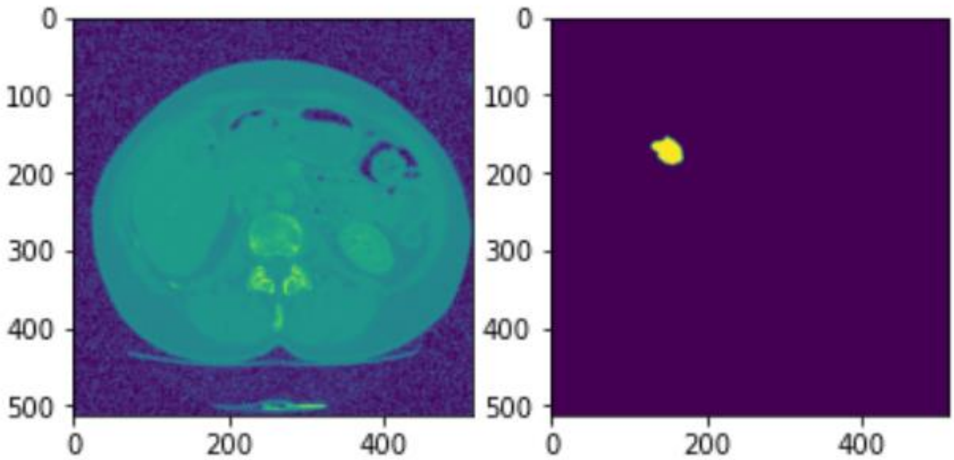

Fig 6: Liver ad liver mask image

5.2 Pre-processing and application of optimisers

The data is pre-processed with the methods like, array initialization, vectorisation, and normalisation. After that the optimizers are applied to the code like, Adam optimiser is generally applied all the code and GWO and PSO applied at the selected model as well for optimization of data for modelling.

5.3 Model application

The model U-net run as a base model. and inception applied as a backbone for the model. Then same has been repeated in terms of ResNet18 as well and the following PSO and GWO applied to the ResNet combination of final model. The study obtained the training accuracy of the model like this below:

	loss	iou_score	f1-score	AUC	val_loss	val_iou_score	val_f1-score	val_AUC
195	0.105644	0.962801	0.981023	0.998498	0.110319	0.927766	0.962529	0.999115
196	0.104297	0.952096	0.975434	0.999930	0.102287	0.944952	0.971696	0.999143
197	0.098408	0.965469	0.982424	0.999634	0.097067	0.957224	0.978144	0.999489
198	0.103684	0.959962	0.979491	0.999903	0.102076	0.935058	0.966423	0.999510
199	0.096146	0.963541	0.981432	0.999608	0.095115	0.961374	0.980299	0.997673

Fig 7: values in evaluation

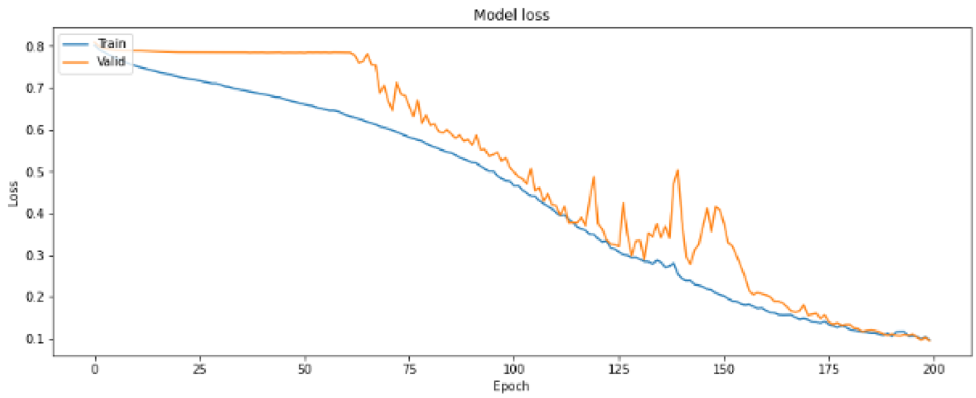

Fig 8: Loss graph for training

6 Evaluation

6.1 Case Study 1

Aim: The aim of the first experiment is to compare the algorithms with the dataset, where the study comparing the U-Net + ResNet18 and Inceptionv3 +U-Net.

The steps followed for the first experiment is listed below:

1. The dataset is loaded and several pre-processing steps like, data array initialisation, vectorisation have been done.
2. The feature extraction is done using the U-Net architecture which takes the small and spatial details of the liver.
3. The model U-Net is applied as base model and on top Inceptionv3 is applied and same process has been done to ResNet18 as well.
4. The data is split into training and testing dataset and the training of the model is run with epochs of 100 with batch size 16.
5. The model is tested for the statistical evaluation metrics like accuracy, sensitivity etc. to find out the model ability.

The Results are discussed below: The modelling has been done with both the hybrid models and it is certain that, the ResNet18 has acquired highest accuracy while compared to the InceptionV3. The other evaluation methods are being calculated here to find out which model performs better than the other.

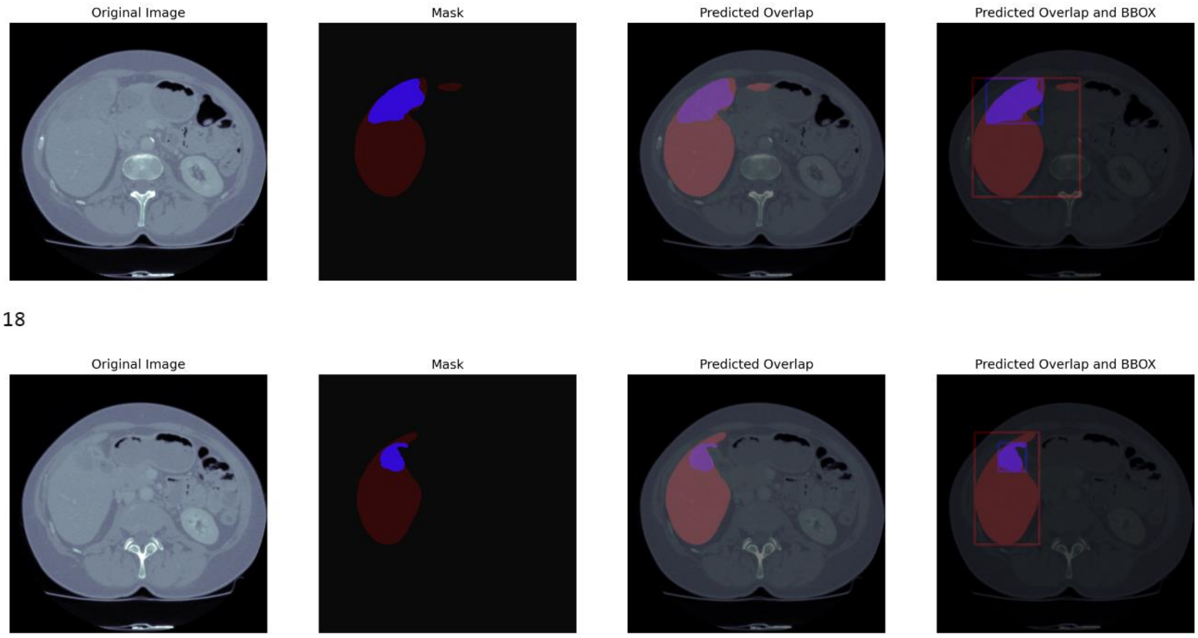

Fig 9 : Predicted outcome of tumor by ResNet18

	loss	accuracy	binary accuracy	mAP	false negatives	false positives	true negatives	true positives	auc	Specificty	Sensitivity
Train	0.394693	0.999368	0.999368	0.524270	13460.0	945.0	22702362.0	89761.0	0.974702	0.999958	0.869600
Test	0.359749	0.999151	0.999151	0.513236	5182.0	606.0	6779880.0	30076.0	0.966074	0.999911	0.853026
Valid	0.343501	0.999058	0.999058	0.498631	3710.0	241.0	4170205.0	20148.0	0.961787	0.999942	0.844497

Fig 10 : Results values of ResNet18

The Model Resnet18 have shown better accuarcy of .99 and it also have good values in mAp , AUC and specifitcty and when compared to model inceptionv3 , it is more balanced in terms of false positive and false negative values and hence , Study selected Resnet18 model hybrid combination with U-Net as the best.

6.2 Case Study 2

Aim: The aim of second experiment is to apply grey wolf optimisation and particle swarm optimisation to produce more balanced result on the selected hybrid model of ResNet 18.

The steps followed for the second experiment is listed below:

1. The dataset is loaded and several pre-processing steps like, data array initialisation, vectorisation have been done like before and we also apply the PSO and the same is done to GSO as well.
2. The feature extraction is done using the U-Net architecture which takes the small and spatial details of the liver and PSO and GSO also makes a part in it.
3. The selected hybrid model of ResNet18 is being tested for the better results with the GSO and PSO variants in the split training data with 200 epochs and batch size of 16.
4. The model is tested for the statistical evaluation metrics like accuracy, sensitivity etc. to find out the model ability and results are compared.

The Results are discussed below: The selected model of resenet18, performs better with the GSO showing the accuracy of .99 percentage, with more balanced scores in the false positive and sensitivity values.

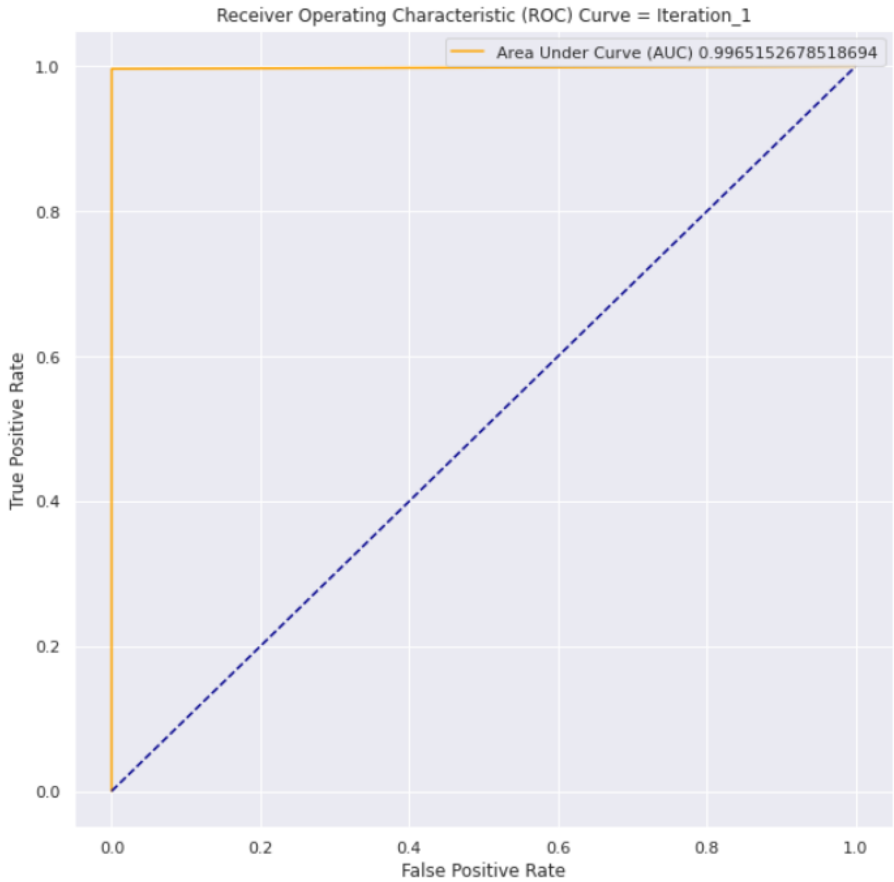

Fig 11: FP and TP graph

	loss	accuracy	binary accuracy	false negatives	false positives	true negatives	true positives	Specificty	Sensitivity
Train	0.115259	0.999809	0.999809	375.0	826.0	6190337.0	99918.0	0.999866	0.996251
Test	0.098668	0.999767	0.999767	118.0	371.0	2056641.0	40022.0	0.999819	0.997036
Valid	0.110008	0.999812	0.999812	62.0	184.0	1288632.0	21842.0	0.999856	0.997124

Fig 12: Resnet with GWO

	loss	accuracy	binary accuracy	false negatives	false positives	true negatives	true positives	Specificty	Sensitivity
Train	0.210517	0.999720	0.999720	464.0	1299.0	6189864.0	99829.0	0.999790	0.995364
Test	0.189893	0.999226	0.999226	550.0	1073.0	2055939.0	39590.0	0.999478	0.986274
Valid	0.209373	0.999298	0.999298	352.0	568.0	1288248.0	21552.0	0.999559	0.983886

Fig 13: Resnet with PSO

The Fig of false positive rates of the GWO and sensitivity and other values shows that, GWO hybrid model gives more balanced results than the PSO model, hence we are taking the **GWO+ResNet18+U-Net** model as the final model.

6.3 Discussion

The project was about to find out the best for tumor detection on the dataset from Ircad and The study achieved the same results. First the dataset was analysed to find out the best model with the architecture U-Net and Inception V3 and the ResNet18 as well, after that we have found that the best model would be Resnet18 as it has accuracy of 99% with showing mAp value of 0.49. The model has also shown that the false positive values are less compared to the Inception hybrid model. As we analysed the specificity as 0.99 which is a good value compared with model2. The sensitivity should be higher as its proves that the model is reliable and here, we have the value as .98 as the model2 have low value. The final selected was Resnet hybrid model which was again compared with GWO and PSO optimisers application. The GWO has shown the more balanced version with accuracy of 0.99 where the sensitivity is higher with 0.99. The final model shows that, it is better than any other model existing in the study. It also proves to be better as a model in the field of study. The model we have selected was applied with high number of epochs with we have resulted the F1_Score of 0.98, which is a comparable score in the study. The below table shows the details about the scores project obtained from the study, and it shows the model has produced a great result.

Evaluation metrics	Values
F1_Score	0.98
Accuracy	0.99
Loss	0.11
False Positive value	184.0
Sensitivity	0.99

Table 4: Evaluation metrics values

7 Conclusion and Future Work

The study was conducted to establish a best model for liver segmentation purpose for tumor detection. The results have proven that we have got a best model with 99% accuracy, which shows that it one of the best models for prediction of segmentation of tumor detection. The model will help many medical practicians and it can be used in the radio therapy treatment and all, and it will serve the medical filed for diagnosis purpose. The intention of the study was to contribute to the medical imaging field a better mechanism for the liver tumor detection automation and it has been done perfectly.

The work can be extended in future to provide a better view by adding more segmentation features and architectures and by exploring different dataset application. The research can be made more effective in feature by adding more feature extraction methods which will reduce the errors and will give a model where nearly no human intervention required.

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