Original Article

Identifying the Porous Bones in CT Scan Dataset Bone using Enhanced Residual Network over Traditional Convolutional Neural Network

Jagadeesh A[1], Senthil Kumar R[2]

[1]Research Scholar, Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, Tamilnadu. India, Pincode: 602105.
[2]Project Guide, Corresponding Author, Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, Tamilnadu. India, Pincode: 602105.

Abstract

Aim: The aim of this study is to identify the porous bones by using the proposed Enhanced Residual Network over Traditional CNN Algorithm. **Materials and Methods:** Sample groups that are considered in this project is CT Scan dataset that can be classified into two, one for Enhanced Residual Network and other for Traditional CNN, Dataset are tested using 233.9s for G-power to determine the sample size and for train set analysis.Nearly 215 CT Scan images have been used in each group for testing of cancer. **Results:** Enhanced Residual Network has better efficiency(79%) when compared to Traditional CNN algorithm efficiency(70%). Statistical significance difference (two-sided) is 0.01 ($p<0.05$). **Conclusion:** Enhanced Residual Network algorithm performed significantly better than the Traditional CNN algorithm.

Keywords
Bone Cancer Detection, Porous Bones, Enhanced Residual Network, Traditional CNN, Machine Learning, CT Scan.

DOI: 10.47750/pnr.2022.13.S04.190

INTRODUCTION

The main aim of this research is to identify Porous bones using CTScan data using Enhanced Residual Network Algorithm and to compare proposed algorithms with Traditional CNN Algorithm. In this situation, the goal of the study is to increase the accuracy of early detection of bone cancer and a machine learning approach for detecting and visualizing malignancy zones in entire slide images of bone tumors. Within human bodies, a variety of diagnostic imaging technologies are used to detect disease or polluted tissue. In both men and women, cancer is the leading cause of mortality.(Lee and Fujita 2020) Early identification of cancer has the ability to completely cure the disease.The necessity for ways to detect the presence of a cancer nodule in its early stages has been highlighted since bone cancer is caused by the uncontrolled development of bone structures.(Suzuki et al. 2022) In a stage known as metastatic disease, the tumor develops beyond the bone and may spread to other regions of the body. (Nayak et al. 2021) Many carcinomas, or cancers that grow from epithelial cells, develop in the bone.Among the various ailments, cancer can be a dangerous one. Among all tumors, bone cancer may be a major cause of death. Porous bones is a condition marked by rapid bone turnover, (Bourouis, Chennoufi, and Hamrouni 2013)decreased bone mass, and skeletal fragility, all of which increase the risk of fracture. It happens when the body loses minerals like calcium quicker than the bones can replace them, causing bone thinning. It usually remains unrecognized until it's too late, once fragility fractures have formed. (Heymann 2021)Uncontrolled cell division in the bone causes the disease, which is malevolent and malignant. The majority of bone cancer is a life-threatening and often occurring malignancy. (Kose and Alzubi 2020) Some of the best applications include identifying the X-ray images of bones in order to determine the porous bones location, discovering early stages of bone cancer and improving life expectancy.
There are around 98 IEEE papers and 156 google scholar papers have been published over the past 5 years. The most cited article is “Bone Cancer Detection at an earlier stage using convolutional neural network ”. (Bourouis, Chennoufi, and Hamrouni 2013). Cancer arises when the body's cells go rogue. Almost every cell in the body has the potential to become a tumour and spread throughout the body. The cells of the bones are where essential bone malignancy begins. (Xu et al. 2018) Tumor cells are cells in the bone that have been proved to be dangerous. The focus of this segment is on the significance of bone growth. The great majority of people with tumour cells in their bones do not have correctly built bones. (Mehta and Sebro 2019) Their bones contain cancer cells that have migrated from a tumour elsewhere in their body.Illness cells have moved from a tumour elsewhere in the body to

their bones. This disorder is known as auxiliary or metastatic bone disease. (Krishnan Unni and Inwards 2010). The above most cited article is best compared to the other articles.
Our institution is passionate about high quality evidence based research and has excelled in various fields (Devarajan et al., 2021; Dhanraj & Rajeshkumar, 2021; Kamath et al., 2020; Nandhini et al., 2020; Parakh et al., 2020; Perumal et al., 2021; Pham et al., 2021; Sathiyamoorthi et al., 2021; Tesfaye Jule et al., 2021; Uganya et al., 2021). In the existing research they didn't identify efficient accuracy for calculating time. (Sharma et al. 2021). Screenings have a number of drawbacks, including false positive and false negative screening results that lead to unneeded investigations. A misleading test result can also cause a hidden malignancy to go undiscovered. Using GGD study, the paper offered a way for distinguishing the size and stages of the discovered disease in bone cancer cells.The approach is similar to how the human brain creates hierarchical learning representation by layering the most representative and useful elements. These methods demonstrate classic approaches to some of the most difficult problems, such as cancer detection and object detection. The machine learning framework utilized here is convolutional neural networks (CNNs). The main aim is to identify porous bones by using Traditional Convolutional Neural Network over Enhanced Residual network Algorithm.

MATERIALS AND METHODS

The research work was performed in the Image Processing Laboratory, Department of Computer Science and Engineering, Saveetha School of Engineering, SIMATS. The proposed work contains two groups. Group 1 is taken as Enhanced Residual Network and group 2 is taken as Traditional CNN. The Enhanced Residual Network algorithm and Traditional CNN algorithm were evaluated a different number of times with a sample size of 10 with confidence interval of 95%, and with pretest power of 81% and maximum accepted error is fixed as 0.05.
After dataset collection,the null values and uncleared content in the datasets were removed by preprocessing and data cleaning steps.After cleaning and preprocessing the data,an ideal input for the detection model is produced, the input images depends on the mean pixel density value and image id. which are processed into the detection model using opencv library and efficiency of both Enhanced Residual Network and Traditional CNN algorithm is calculated.
Testing setup for this proposed system used a Jupyter notebook and pycharm. Jupyter notebook is a software which is used for creating the Osteoporosis Detection with Enhanced Residual Network model and Traditional CNN. Hardware configuration for this proposed system is Intel core i5 8th gen processor and requires 4GB random access memory and 256GB Solid state drive used. The configuration of the system is windows 10 operating system and jupyter notebook software and python programming language 3.8.3.

Testing Procedure for Bone Cancer Detection with Enhanced Residual Network and Traditional CNN

Step 1: Preprocessing

Almost all recorded images are affected by noise in most cases, the result is poor quality. The algorithm must extract the relevant portion of the photos with no noise, and blurriness from the photos, then preprocessing procedures such as filtering, histogram equalization, and so on must be used. The photos are preprocessed using Python software. In Fig.3. represents the block diagram of the testing procedure to detect cancer. The primary goal of preprocessing photos is to eliminate the extravagance that can be found in scanned images. Every image is preprocessed in order to reduce noise and improve quality. In Fig.4.represents the normal and preprocessed image.

Step 2: Feature Selection

This procedure selects a small number of useful characteristics for future use. Following preprocessing, genetic algorithms are used to choose features from the preprocessed image.

Step 3: Feature Extraction

Feature extraction can accurately predict the amount of resources required from a big quantity of data. Following the selection of characteristics, features must be extracted. It has a significant function to play in that it employs algorithms and approaches to identify the various sections and attributes that must be removed.

Step 4: Training and Testing Classifier

After the feature extraction step, the training process is done. Training step involves CT Scan Dataset as input to the classifier to generate indices. In the test classifier it is possible to import different and more datasets to test the accuracy of the classifier. Testing process is used to detect if the bone has cancer or not. In this step the classifier shows the result of cancer if it shows 1 means cancer and 0 means no cancer.

Step 5: Finding the cancer or no cancer

Using the Bone Cancer Detection with Enhanced Residual Network algorithms and Traditional CNN to predict the images and identify the cancer based on the mean pixel density. In Fig.5.describes the dataset of the CTscan images.

Enhanced Residual Network

The Residual Neural Network (ResNet) is a structure-based type of artificial neural network (ANN) known from the pyramidal cells of the cerebral cortex. The rest of the neural network does this by skipping some layers using skip connections or shortcuts. You can stack the remaining blocks one after another without impacting performance. This allows you to build a very deep network.

Inputs: CT scan data set **Output:**
Selected features and Accuracy.

```
Get CTScan()
CTS_slices=pd.read_csv("cnn1.csv")
read_Img=CTS_slices
Img<-exp(Img)
for Img i to n
        img_ids = Img.str.split('.').str[0]
        assert df_centers.img_id.equals(img_ids)
        df_train = pd.DataFrame(mat_images, columns=['pxl' + str(i) for i in
                                range(img_ids)])
        df_train = pd.concat([df_train, df_train_hflip, df_train_vflip],
                            ignore_index=True)
        X = df_train.drop(columns=['img_id', 'cx', 'cy']).values.reshape((-1,
    IMG_HEIGHT, IMG_WIDTH, IMG_CHANNELS))
        Y = df_train[['cx', 'cy']].values
X_train,X_test,y_train,y_test<-split features set and labels into train subset and test
                                                    subset
history = model.fit(X_train,y_test<-split features set and labels into train subset and
                                                    test subset
V<-ResNet(X_train,y_train)
score<-evaluate(i,y_test,v)
return score
```

Traditional Convolutional Neural Network

A convolutional neural network, also known as CNN or ConvNet, is a class of neural networks that specializes in processing data in grid-like topologies such as images.Each neuron functions in its own receptive field and is connected to other neurons to cover the entire field of view. Convolutional neural networks (CNN / ConvNet) are the most commonly used class of deep neural networks for the analysis of visual images.

Inputs: CT scan dataset **Output:**
Selected features and Accuracy.

```
Get CTScan()
CTS_slices=pd.read_csv("cnn1.csv")
read_Img=CTS_slices
Img<-exp(Img)
for Img i to n
        img_ids = Img.str.split('.').str[0]
        assert df_centers.img_id.equals(img_ids)
        df_train = pd.DataFrame(mat_images, columns=['pxl' + str(i) for i in
                                range(img_ids)])
        df_train = pd.concat([df_train, df_train_hflip, df_train_vflip],
                            ignore_index=True)
        X = df_train.drop(columns=['img_id', 'cx', 'cy']).values.reshape((-1,
    IMG_HEIGHT, IMG_WIDTH, IMG_CHANNELS))
        Y = df_train[['cx', 'cy']].values
X_train,X_test,y_train,y_test<-split features set and labels into train subset and test
                                                    subset
history = model.fit(X_train,y_test<-split features set and labels into train subset and
                                                    test subset
V<-CNN(X_train,y_train)
score<-evaluate(i,y_test,v)
return score
```

Dataset is collected from CT Scan Dataset. In the dataset 70% is used for training and 30% used for testing. The Enhanced Residual Network(ResNet) and Traditional CNN algorithms were evaluated with respect to training, and tests were conducted with the required parameters to improve the accuracy percentage.

Statistical Analysis

Statistical software used in the study is IBM SPSS version 26. The independent sample T-test calculation for analyzing equal variance, standard error, and levene's test are evaluated. Attributes like image id, mean density value, pixel density, detection and class are dependent variables. Independent sample T-test has been carried out for evaluating the accuracy.

RESULTS

In this proposed system it was observed that Enhanced Residual Network appears to have better accuracy than the Traditional CNN algorithm.Table 1 represents the attributes of CTscan Dataset.In Fig.1. represents the architecture for identifying porous bones estimation for each CT Scan image using Enhanced Residual Network algorithm. Table 2 shows the sample accuracy of ResNet and Traditional algorithms.ResNet uses optimization procedures to deliver high accuracy. Table 3 shows the statistical calculation such as mean, standard deviation and standard error mean for Enhanced Residual Network and Traditional CNN algorithms. It is inferred that the deviation for T-test is far lesser than the comparison algorithm. Moreover, the accuracy value of ResNet is around 79.9. while the loss is around 18.40, which seems to be superior to the Traditional CNN classifier. In Table 4, it was observed that the Levens test for equality of variance and its significance for ResNet is 1.778 and 0.329, respectively and standard error difference and confidence interval are lower than Traditional CNN classifiers. Mean accuracy and mean loss graph is depicted in Fig. 2. ResNet seems to appear better for the given CT Scan dataset of Bone Cancer Detection.

DISCUSSION

The proposed system provides better porous bones identification using a Enhanced Residual Network with a count vectorizer with over 79.9% accuracy compared to traditional convolutional neural network algorithms.

There are similar papers to analyze the bone density of porous bones using machine learning algorithms.In this research paper uses a screening and identifying method to identify cancer.(Moreira et al. 2021)Cancer is a disease that affects people of all ages and is fatal. More than one-third of the population will develop cancer at some time in their lives. The basic goal of reviewing diagnostic medical procedures such as X-rays, CT scans, and PET scans is to identify the affected area in the bone tract, i.e., the aberrant growth and phase of the disease. (Rühling et al. 2021)Because the scanned images may not have a high resolution due to the enormous number of layers per pixel and noise, it is required to reduce the noise by pre-processing them with a medium filter.Using a genetic approach, some properties of the preprocessed image are analyzed and extracted by CNN. A CNN classifier is used to classify and record the recovered images in order to assess the stage of the disease, (Chen et al. 2021)which aids the doctor in making therapy suggestions. The proposed method's results demonstrate a better rate of early detection of bone cancer.

Machine learning has been shown to be useful in the disciplines of medical imaging diagnosis, sickness prediction, and bone cancer diagnosis, as well as risk assessment. In this study, it is found that there are various scientific issues that need to be solved.(Almarzouki 2022) Computerized health care systems, for example, have been shown to be quite successful in diagnosing early-stage bone cancer, particularly in countries like India, where the mortality rate is high and the doctor-patient ratio is low. Medical imaging is used to diagnose cancer as a result of this event.

CONCLUSION

The Residual Network algorithm detects cancer with better accuracy of 79% compared to Traditional CNN algorithm with 70%.

Declarations

Conflict of Interests

No conflict of interest in this manuscript.

Author Contribution

Author Jagadeesh Atthipatla was involved in data collection, data analysis, and manuscript writing. Author RSK was involved in conceptualization, guidance and critical review of manuscript.

Acknowledgments

The authors would like to express their gratitude towards Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences (Formerly known as Saveetha University) for providing the necessary infrastructure to carry out this work successfully.

Funding

We thank the following organizations for providing financial support that enabled us to complete the study.

1. STEP UP Technologies, Chennai
2. Saveetha University
3. Saveetha Institute of Medical and Technical Sciences.

4. Saveetha School of Engineering.

REFERENCES

1. Almarzouki, Hatim Z. 2022. "Deep-Learning-Based Cancer Profiles Classification Using Gene Expression Data Profile." Journal of Healthcare Engineering 2022 (January): 4715998.
2. Bourouis, Sami, Ines Chennoufi, and Kamel Hamrouni. 2013. "Multimodal Bone Cancer Detection Using Fuzzy Classification and Variational Model." Progress in Pattern Recognition, Image Analysis, Computer Vision, and Applications. https://doi.org/10.1007/978-3-642-41822-8_22.
3. Chen, Pu, Run Chen Xu, Nan Chen, Lan Zhang, Li Zhang, Jianfeng Zhu, Baishen Pan, Beili Wang, and Wei Guo. 2021. "Detection of Metastatic Tumor Cells in the Bone Marrow Aspirate Smears by Artificial Intelligence (AI)-Based System." Frontiers in Oncology 11 (September): 742395.
4. Heymann, Dominique. 2021. Bone Cancer: Bone Sarcomas and Bone Metastases - From Bench to Bedside. Academic Press.
5. Kose, Utku, and Jafar Alzubi. 2020. Deep Learning for Cancer Diagnosis. Springer Nature.
6. Krishnan Unni, K., and Carrie Y. Inwards. 2010. Dahlin's Bone Tumors: General Aspects and Data on 10,165 Cases. Lippincott Williams & Wilkins.
7. Lee, Gobert, and Hiroshi Fujita. 2020. Deep Learning in Medical Image Analysis: Challenges and Applications. Springer Nature.
8. Mehta, Samir D., and Ronnie Sebro. 2019. "Random Forest Classifiers Aid in the Detection of Incidental Osteoblastic Osseous Metastases in DEXA Studies." International Journal of Computer Assisted Radiology and Surgery 14 (5): 903–9.
9. Moreira, Larissa F., Thais C. Mussi, Marcelo L. da Cunha, Renée Z. Filippi, and Ronaldo H. Baroni. 2021. "Accuracy of Ga-PSMA PET/CT for Lymph Node and Bone Primary Staging in Prostate Cancer." Urologic Oncology, December. https://doi.org/10.1016/j.urolonc.2021.11.007.
10. Nayak, Janmenjoy, Margarita N. Favorskaya, Seema Jain, Bighnaraj Naik, and Manohar Mishra. 2021. Advanced Machine Learning Approaches in Cancer Prognosis: Challenges and Applications. Springer Nature.
11. Rühling, Sebastian, Fernando Navarro, Anjany Sekuboyina, Malek El Husseini, Thomas Baum, Bjoern Menze, Rickmer Braren, Claus Zimmer, and Jan S. Kirschke. 2021. "Automated Detection of the Contrast Phase in MDCT by an Artificial Neural Network Improves the Accuracy of Opportunistic Bone Mineral Density Measurements." European Radiology, October. https://doi.org/10.1007/s00330-021-08284-z.
12. Sharma, Ashish, Dhirendra P. Yadav, Hitendra Garg, Mukesh Kumar, Bhisham Sharma, and Deepika Koundal. 2021. "Bone Cancer Detection Using Feature Extraction Based Machine Learning Model." Computational and Mathematical Methods in Medicine 2021 (December): 7433186.
13. Suzuki, Taiki, Akitoshi Katsumata, Yusuke Mastumoto, Masumi Komatu, Yusuke Oomura, Masahiro Okamura, Sakiko Mizuno, Ukei Anazawa, and Takeshi Nomura. 2022. "Features of Mandibular Cortical Bone Morphology in Osteoporotic Fracture Patients." Oral Radiology, February. https://doi.org/10.1007/s11282-022-00596-0.
14. Xu, Lina, Giles Tetteh, Jana Lipkova, Yu Zhao, Hongwei Li, Patrick Christ, Marie Piraud, Andreas Buck, Kuangyu Shi, and Bjoern H. Menze. 2018. "Automated Whole-Body Bone Lesion Detection for Multiple Myeloma on Ga-Pentixafor PET/CT Imaging Using Deep Learning Methods." Contrast Media & Molecular Imaging 2018 (January): 2391925.

TABLES AND FIGURES

Table 1. Attributes of CT Scan Dataset

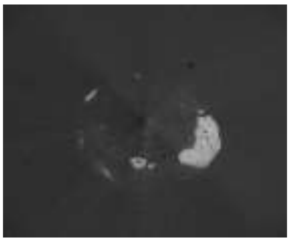
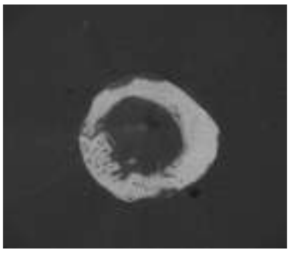
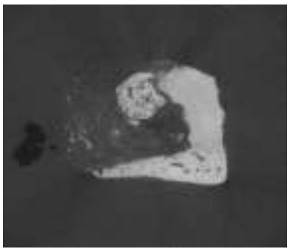
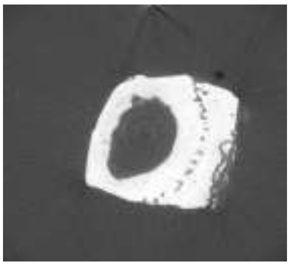
S.No	Images	Mean Intensity	Experimental	Prediction
1		248	Not Cancer	False
2		237	Cancer	True
3		244	Cancer	True
4		236	Cancer	True
5		242	Not Cancer	False

Table 2. Efficiency of Enhanced Residual Network and Traditional Convolutional Neural Network. The Residual Network algorithm is 9% more efficient than the Traditional Convolutional Neural Network algorithm.

Sample(N)	**Enhanced Residual Network Algorithm**	**Traditional Convolutional Neural Network Algorithm**
	Accuracy(%)	**Accuracy(%)**
1	79	70
2	78	69
3	76	67
4	74	65
5	73	64
6	71	62
7	69	60
8	68	58
9	66	57
10	64	55

Table 3. Comparison of the accuracy of Bone Cancer Detection of Enhanced Residual Networks and Traditional Convolutional Neural Networks. The Residual Network algorithm had the highest accuracy (79.9). Traditional Convolutional Neural Networks had the lowest accuracy (70.9).

T-Test:

Group Statistics

GROUP		**N**	**Mean**	**STD Deviation**	**STD Error mean**
ACCURACY	**Enhanced Residual Network**	10	79.90	4.725	1.494
	Traditional CNN	10	70.90	5.507	1.741

Table 4. Independent Sample T-Test is applied for the sample collections by fixing the level of significance as 0.05 with confidence interval as 95%. After applying the SPSS calculation, the Residual Network has accepted a statistically significant value ($p<0.05$).

	Equal Variances	**Levene's Test for Equality of Variance**		**Levene's Test for Equality of Variance**					
		F	Sig.	t	df	Sig.(2-	Mean	Std. Error	95%

						tailed)	Difference	Difference	Confidence Interval of the Difference	
									Lower	Upper
Accuracy	Assumed	.571	.459	3.923	18	.001	9.000	2.294	4.180	13.820
	Not Assumed			3.923	17.594	.001	9.000	2.294	4.172	13.828

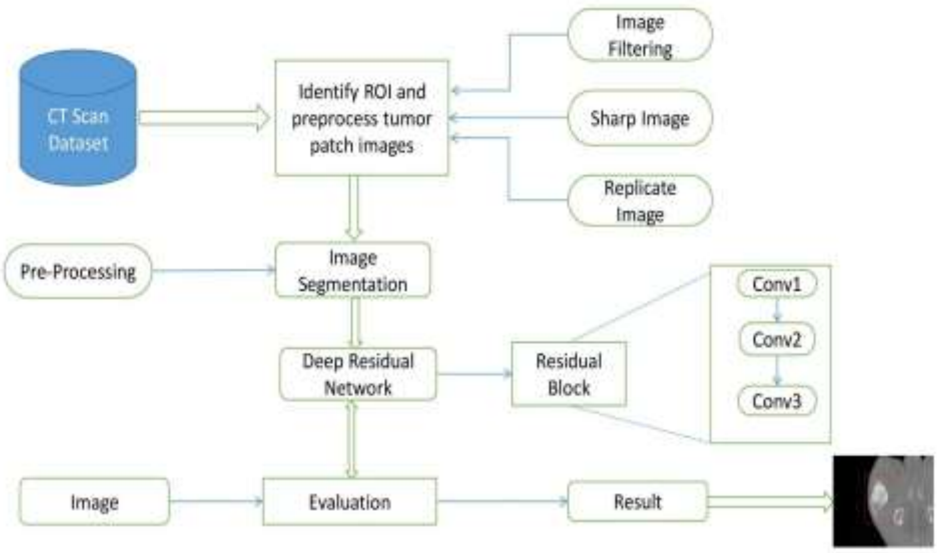


Fig. 1. Architecture for identifying porous bones estimation for each CT Scan image using Enhanced Residual Network algorithm, from dataset processing to output of each image.

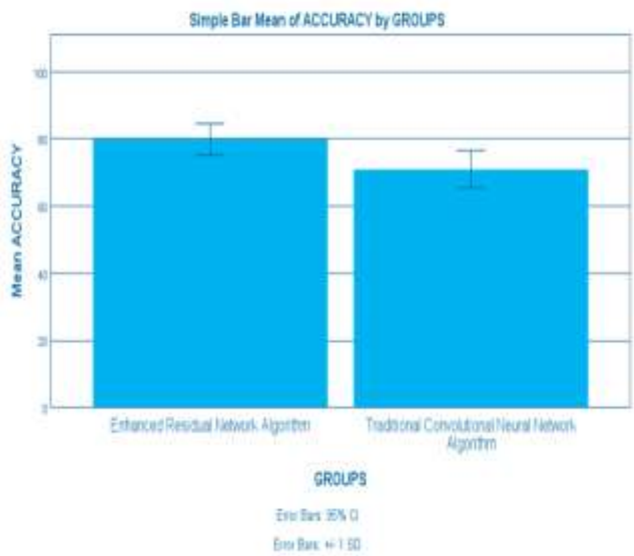


Fig. 2. Bar graph analysis of Enhanced Residual Network algorithm and Traditional Convolutional Neural Network algorithm. Graphical representation shows the mean efficiency of 79% and 70% for the proposed algorithm ResNet and Traditional CNN respectively. X-axis : ResNet vs Traditional CNN, Y-axis : Mean precision ± 1 SD.

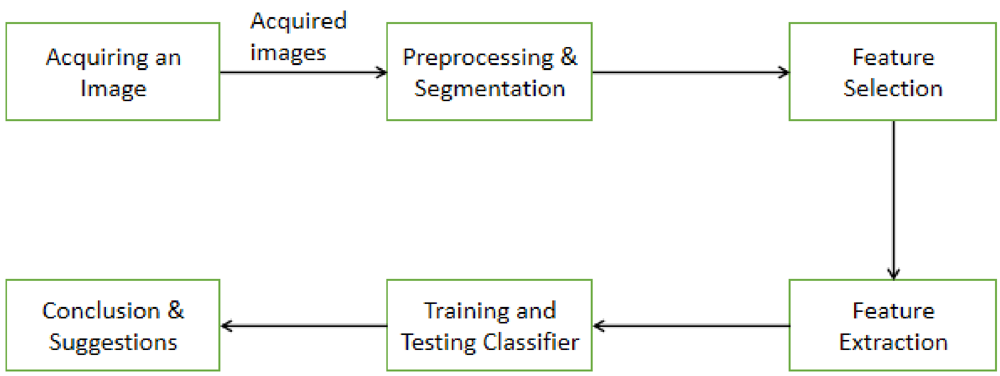


Fig. 3. Block Diagram for Enhanced Residual Network algorithm

Fig.4. a) Normal Image b) Preprocessed Image

Fig. 5. Data stored in dataset of CTscan