AI Technique Using Identification of Brain Tumor and Lung Cancer Diseases

Nitesh Kharose[1], Siddhi Kenjale[2], Sakshi Madhale[3], ChitralekhaChopade[4], Dr.MangeshSalunke[5]
[1,2,3,4,5] *Department of Computer Engineering, JSPM Narhe Technical Campus Pune, Savitribai Phule Pune University, Maharashtra*

***Abstract*— Brain (tumors) is the cause of every sixth death around the world. This makes cancer a second leading cause of death. Globally 42 million people across the world suffer from cancer and this figure is continuously increasing. In India around 2.5 million people are suffering from different types of cancer. If detected in early stage, then with proper treatment it can be cured. This paper presents details of a few methods used for detection of diseases like brain tumor, liver cancer, lung cancer and Spine tumor. This paper also speaks about the different machine learning techniques used to classify the diseases into malignant & benign. Once disease is diagnosed we will recommend the hospital as well as precautions for that specific disease. In this paper, we will utilize AI calculations and profound realizing which can be used for health care diagnosis. In this paper we are proposed the disease identification using images of lung cancer and brain tumor. Accordingly we are recommending the precautions and hospital to the patient. In this paper we are detecting the disease by using convolutional neural network for classifying the disease and get 92.6% accuracy on 100 epochs. We are recommending the hospital by using support vector machine.**

Index Terms: **Brain Tumor, Lungs Cancer, Multi Disease Detection, Convolutional Neural Network, Neural Network, Deep Learning, Support Vector Machine.**

I.INTRODUCTION

In spite of several developments in the field of diagnosis of cancer, still tumor is one of the most dangerous diseases. Lung Cancer is the second most popular reason of death not only in India, but across the world. Diagnosis of tumor is a very crucial task. Due to this reason, detection and treatment of cancerous tumors is one of the major research areas. The rate of survival for the patients can be improved, only if the cancer is diagnosed at the early stage and if proper treatment is given soon after the detection of the disease. There are various techniques to capture different types of cancers, to name a few, CT scan, PET scan, Mammograms, Single Photon Emission Computed Tomography (SPECT), MRI, 3D Ultrasound etc. For breast cancer diagnosis, mammograms are used. CT scan, MRI and other techniques are used to detect brain tumors, lung cancer etc. Doctors inspect images to detect tumors.

The imaging technique considered is mammogram and the classification techniques used are Feed forward back propagation, Extreme Learning Machine (ELM) ANN, back propagation ANN, Particle Swarm Optimized Wavelet Neural Network and CNN based on deep learning. For brain tumors, imaging technique used is MRI and CT scan and the classification techniques considered are Level Set, K means Algorithm, SVM, Fuzzy C-means, Adaboost, Naïve Bayes classifier and ANN classifier. For lung cancer medical imaging technique used is PET/CT and classification techniques considered are FCM classifier, ANN, Feed Forward ANN, SVM binary classifier and Entropy degradation method. For spine tumor detection medical imaging technique considered are MRI and classification methods used are ANN, SVM and Multilayer perceptron neural network.

II.LITERATURESURVEY

Chao Ma, Gongning Luo, and Kuanquan Wang Waghmodeet al. [1] stated that, this work, we introduce a new methodology that combines random forests and active contour model for the automated segmentation of the gliomas from multimodal volumetric MR images. Specifically, we employ a feature representations learning strategy to effectively explore both local and contextual information from multimodal images for tissue segmentation by using modality specific random forests as the feature learningkernels.

OnurOzdemir et al. [2] proposed that d entirely on 3D convolutional neural networks and achieves state-of-the-art performance for both lung nodule detection and malignancy classification tasks on the publicly available LUNA16 and Kaggle Data Science Bowl challenges. While nodule detection systems are typically designed and optimized on their own, we find that it is important to consider the coupling between detection and diagnosis components.

Anum Masood, Bin Sheng, Po Yang, Ping Li, [3] proposed that experimented enhanced multidimensional Region-based Fully Convolutional Network (mRFCN) based automated decision support system for lung nodule detection and classification. The mRFCN is used as an image classifier backbone for feature extraction along with the novel multi-Layer fusion Region Proposal Network (mLRPN) with position-sensitive score maps (PSSM) being explored. They applied a median intensity projection to leverage three-dimensional information from CT scans and introduced deconvolutional layer to adopt proposed mLRPN in the architecture to automatically select potential region-of-interest.

Khan Muhammad, Salman Khan [4] stated that an in-depth review of the surveys published so far and recent deep learning-based methods for BTC. Our survey covers the main steps of deep learning-based BTC methods, including preprocessing, features extraction, and classification, along with their achievements andlimitations.

David N. Louis et al. [5] stated that notable changes include the addition of brain invasion as a criterion for atypical meningioma and the introduction of a soft tissue-type grading system for the now combined entity of solitary fibrous tumor hemangiopericytoma-a departure from the manner by which other CNS tumors are graded. Overall, it is hoped that the 2016 CNS WHO will facilitate clinical, experimental and epidemiological studies that will lead to improvements in the lives of patients with braintumors.

PärSalander et al. [6] proposed that Most spouses witnessed months of global dysfunction preceding the symptom leading to physician consultation. The patient factors ‘less alien symptoms’, ‘personality change’ and ‘avoidance’; the spouse factors ‘spouse's passivity’ and ‘spouse's successive adaptation’; and the physician factors ‘reasonable alternative diagnosis’, ‘physician's inflexibility’ and ‘physician's personal values’ were identified as obstacles on the pathway to appropriate medical care.

III PROPOSED METHOD AND ALGORITHM

A. Proposed Methodology

In a proposed system, we are proposing experiment on brain tumor and lung cancer diseases with limited set of supervised data.

We are proposing a Convolutional neural network based multimodal disease risk prediction model for limited diseases with higher accuracy. We are solved accuracy issue in diagnosis of lung cancer with accurate stage predictions. We also worked on brain tumor detections by machine evaluations depends on sizes in mm.

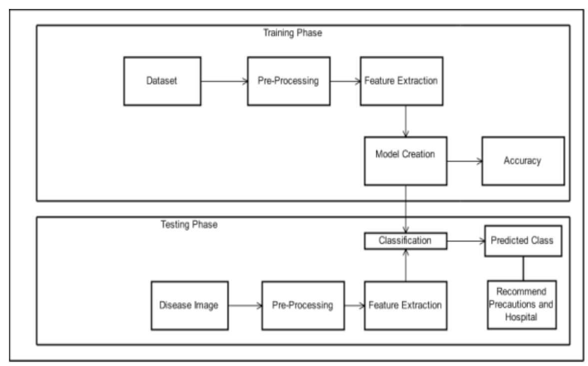

Figure1. Proposed Architecture

In this project we are collecting the data from kaggle platform. We require two different datasets one for disease lung cancer and another for brain tumor prediction based on image as shown in figure2.

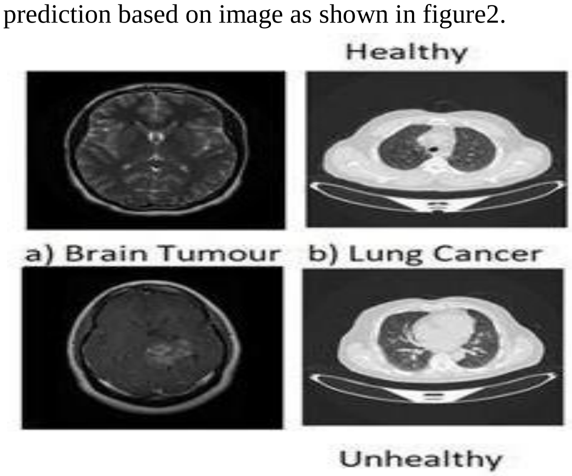

Figure2. Dataset

1. Convolutional Neural Networks(CNN)

Convolutional Neural Networks (which are additionally called CNN/ConvNets) are a kind of Artificial Neural Networks that are known to be tremendously strong in the field of distinguishing proof just as pictureorder.

Four main operations in the Convolutional Neural Networks are convolutional layer, max pooling layer, relu and fully connected layer.

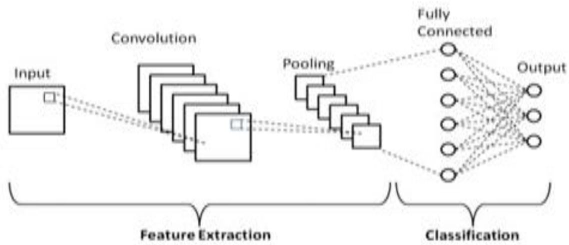

Figure3. CNN Architecture

(i) Convolution

The principle utilization of the Convolution activity if there should be an occurrence of a CNN is to recognize fitting highlights from the picture which goes about as a contribution to the primary layer. Convolution keeps up the spatial interrelation of the pixels. This is finished by fulfilment of picture highlights utilizing miniscule squares of the picture. Convolution equation. E very picture is seen as a network of pixels, each having its own worth. Pixel is the littlest unit in this picture grid. Allow us to take a 5 by 5(5*5) framework whose qualities are just in twofold (for example 0 or 1), for better agreement. It is to be noticed that pictures are by and large RGB with upsides of the pixels going from 0 - 255 i.e 256 pixels.

(ii). ReLU

ReLU follows up on a rudimentary level. All in all, it is an activity which is applied per pixel and overrides every one of the non-positive upsides of every pixel in the component map by nothing as shown in figure3.

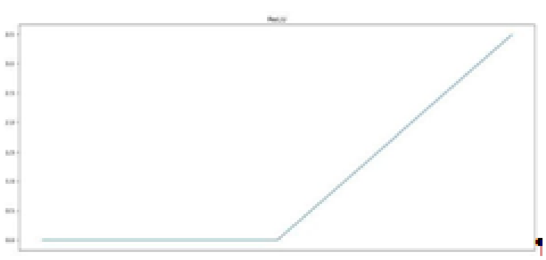

Figure4: Relu Activation

It is represented as:

$$f(x)=\begin{cases} 0, if\ x<0 \\ x, otherwise \end{cases} \quad (1)$$

(iii). Pooling or sub-sampling

Spatial Pooling which is likewise called sub-sampling or down sampling helps in lessening the elements of each element map yet even at the same time, holds the most important data of the guide. Subsequent to pooling is done, in the long run our 3D element map is changed over to one dimensional component vector.

2. SVM

Generally the use of machine learning algorithm is used for the recommendation of hospital. In this paper, the support vector machine will suggest the hospital. SVM is a supervised machine learning algorithm which works based on the concept of decision planes that defines decision boundaries. A decision boundary separates the objects of one class from the object of another class. Support vectors are the data points which are nearest to the hyper-plane. Kernel function is used to separate non-linear data by transforming input to a higher dimensional space as shown in figure5. Given a set of labelled training examples, each belonging to one category. Support Vector Machine builds a model that assigns new examples to one of the category.

SVM cost function is given as:

$$\text{Min}C\sum[y^{(1)}cost_1(\theta^T x^{(i)})+(1-y^{(i)})cost_0(\theta^T x^{(i)})].\ h(x) = \begin{cases} 1, if\ \theta TX\geq 0 \\ 0, otherwis \end{cases} \text{.........} (2)$$

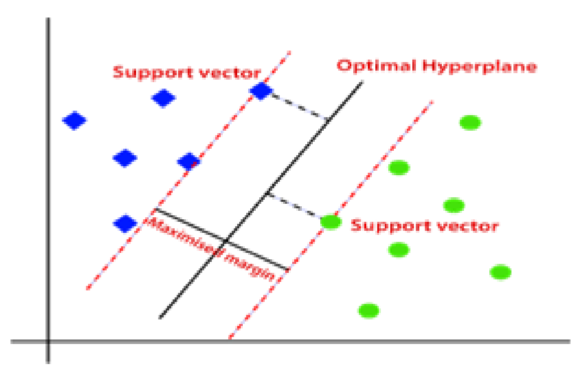

Figure5. SVM Architecture

Where,

x: Training example (featurevector)

m: Number of trainingexamples

n: number of features

θ: parameter vector

C: constant

y: class label.

IV.RESULTS &DISCUSSION

In our experimental setup, as shown in table 1, the total numbers of 319 of trained images for three diseases such as brain tumor, lung cancer 59 new images were tested. These images go through CNN framework by following feature extraction using our image processing module. Then our trained model of classification of diseases get classifies the image into specifies disease. We get the accuracy 92.5% at 100 epochs as shown in fig.4. In that yellow line specifies the validation or test data accuracy and blue line for trained data accuracy.

Sr. No.	Category	Number of Images
1	Training	319
2	Testing	59

Table1. Splitting of Data

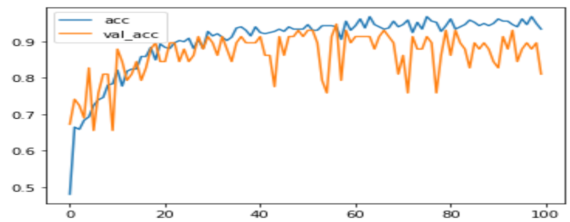

Figure6-a. Accuracy of CNN

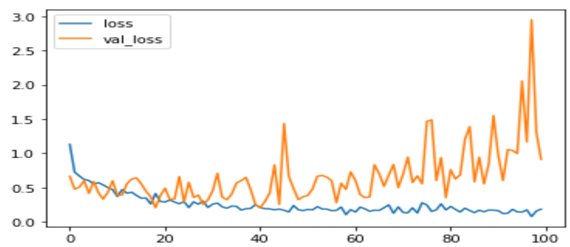

Figure6-b. Loss of CNN

V.CONCLUSION

We are solved Brain Tumor and Lungs Cancer detection system over machine learning and CNN techniques which solves existing accuracy problem as well as reduce death rates by diseases like brain tumor and lung cancer. We get the 92.5% accuracy on CNN for 100 epoch. After detection of disease inform to users that how to prevent from a disease. We recommend the hospital for specific disease by using SVM classifier. For future work, we can implement this technique on some more diseases with rich dataset. Increasing the number of diseases and dataset used for the process can improve the accuracy.

REFERENCE

[1] C. Ma, G. Luo, and K. Wang, "Concatenated and connected random forests with multiscale patch driven active contour model for automated brain tumor segmentation of MR images," IEEE Trans. Med. Imag., vol. 37, no. 8, pp. 1943–1954, Aug.2018.

[2] C.-M. Feng, Y. Xu, J.-X. Liu, Y.-L. Gao, and C.-H. Zheng, "Supervised discriminative sparse PCA for com-characteristic gene selection and tumor classification on multiview biological data," IEEE Trans. Neural Netw. Learn. Syst., vol. 30, no. 10, pp. 2926–2937, Oct.2019.

[3] OnurOzdemir, Rebecca L. Russell "A 3D Probabilistic Deep Learning System for Detection and Diagnosis of Lung Cancer Using Low-Dose CT Scans" IEEE TRANSACTIONS ON MEDICAL IMAGING last revised 21 Jan2020.

[4] Anum Masood, Bin Sheng, Po Yang, Ping Li "Automated Decision Support System for Lung Cancer Detection and Classification via Enhanced RFCN with Multilayer Fusion RPN" IEEE Transactions on Industrial Informatics (Volume: 16, Issue: 12, Dec.2020).

[5] Khan Muhammad; SalmanKhan; Javier Del Ser; Victor Hugo C. de Albuquerque. "Deep Learning for Multigrade Brain Tumor Classification in Smart Healthcare Systems: A Prospective Survey" IEEE Transactions on Neural Networks and LearningSystems (Volume:32, Issue: 2, Feb. 2021).

[6] David N. Louis, Arie Perry, et al., "The 2016 World Health Organization Classification of Tumors of the Central Nervous System: a summary", Acta Neuropathol, Springer may2016

[7] PärSalander, A Tommy Bergenheim, Katarina Hamberg, Roger Henriksson, Pathways from symptoms to medical care: a descriptive study of

symptom development and obstacles to early diagnosis in brain tumour patients, Family Practice, Volume 16, Issue 2, April 1999, Pages 143– 148,