

Brain Tumor Detection Using Deep Learning

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Abstract: *The brain tumor is one of the most dangerous, common and aggressive diseases which leads to a very short life expectancy at the highest grade. Thus, to prevent life from such disease, early recognition, and fast treatment is an essential step. In this approach, MRI images are used to analyze brain abnormalities. The manual investigation of brain tumor classification is a time-consuming task and there might have possibilities of human errors. Hence accurate analysis in a tiny span of time is an essential requirement. In this approach, the automatic brain tumor classification algorithm using a highly accurate Convolutional Neural Network (CNN) algorithm is presented. Initially, the brain part is segmented by thresholding approach followed by a morphological operation. The brain MRI is classified using CNN, Inceptionv3, and Xceptionv3 algorithms. The performance of the system is evaluated using precision, recall, F1 score and accuracy parameter.*

Keywords: Support Vector Machine (SVM) and K-Nearest Neighbor (KNN)

I. INTRODUCTION

MRI is an essential tool in the clinical and surgical environment due to superior soft tissue differentiation, high spatial resolution, contrast and it does not use any harmful ionizing radiation which may affect patients. Cancer develops in a part of the body when cells begin to grow out abnormally. Radiologists examine MRI Images based on visual interpretation to identify the presence of tumor [1].

There might be a possibility when large volume of MRI to be analyzed, then there is a possibility of wrong diagnosis by radiologists because the sensitivity of the human eye decreases with the escalating number of cases, predominantly when only a small number of slices are affected. Hence there is a need for efficient automated systems for analysis and classification of medical images. The MRI image may contain both normal and abnormal images. Feature extraction refers to various quantitative measurement of medical images typically used for decision making regarding the pathology of a structure or tissue. In image processing, feature extraction is a special form of dimensionality diminution [2].

When the input data to an algorithm is too large to be processed and it is assumed to be disgracefully unnecessary, then the input data will be transformed into a compact representation set of features. Brain tumors are abnormal masses in or on the brain. Tumor growth may appear as a result of uncontrolled cell proliferation, a failure of the normal pattern of cell death, or both. Brain tumors can be either primary or secondary. Primary tumors are composed of cells just like those that belong to the organ or tissue where they start. A primary brain tumor starts from cells in the brain. Malignant tumors grow quickly and can spread to surrounding tissues. " Malignancy" or " malignant" almost always refers to cancer.

OBJECTIVES

- Literature survey on techniques and methods to detect and analyze the Brain tumor.
- To explore, collect and select the appropriate brain MRI dataset for brain tumor detection.
- To pre-process the data to make it suitable for further processing.
- To implement the algorithms to classify the brain MRI into glioma, meningioma, pituitary and no tumor
- To calculate, validate and verify the performance of the effective classifier.

- Imaging plays very decisive role in analysis of diagnosis of patients having brain tumors. Integration with Healthcare Systems:
- Primary tumors are composed of cells just like those that belong to the organ or tissue where they start.
- Secondary brain tumors are actually undistributed of cancer cells from somewhere else in the body that have metastasized, or spread to the brain. Verification and Assessment:

II. LITERATURE SURVEY

In this paper, S. Ajikumar and Dr. A. Jayachandran [1] proposed a method consisting of four stages: Pre-processing, feature extraction, feature reduction, and classification. In the first stage, a wiener filter is applied to reduce noise and make the image suitable for extracting the features. In the second stage, the seeded region growing segmentation is used for partitioning the image into meaningful regions. In the third stage, discrete wavelet transformation (DWT) is used to extract the wavelet coefficients from the segmented image. In the next stage, PCA is used to reduce the dimensionality of the wavelet coefficients.

The AdaBoost classifier is used in the classification stage to classify the experimental images into normal and abnormal cases. Our proposed method is evaluated using the metrics of sensitivity, specificity, and accuracy. It produces a better result. Carlos Arizmendi, Alfredo Vellido, et al. [2] proposed a paper addressing such a problem in binary classification, for which the pre-processing of the Magnetic Resonance Spectroscopy (MRS) signal is the most relevant data analysis stage. A combination of the Discrete Wavelet Transform (DWT) for signal decomposition and an energy criterion for signal reconstruction is used to pre-process the MRS data before the feature selection and classification with Bayesian Neural Networks. This system investigates a multi-center, international database of single-voxel

Dipali M. Joshi, Dr. N. K. Rana et al. [3] proposed a system that uses computer-based procedures to detect tumor blocks or lesions and classify the type of tumor using Artificial Neural Network in MRI images of different patients with Astrocytoma type of brain tumor. Image processing techniques such as histogram equalization, image segmentation, image enhancement, morphological operations, and feature extraction have been developed to detect brain tumors in the MRI images of cancer-affected patients. The extraction of texture features in the detected tumor has been achieved using Gray Level Co-occurrence Matrix (GLCM). These features are compared with the stored features in the Knowledge Base. Finally, a Neuro-Fuzzy Classifier has been developed to recognize different brain cancers. The whole system has been tested in two phases: the Learning/Training Phase and the Recognition/Testing Phase.

[4] proposed a paper that consists of second-level discrete wavelet transform decomposition of the image under study, feature extraction from the LH and HL sub-bands using first-order statistics, and subsequent classification with the k-nearest neighbor (k-NN), learning vector quantization (LVQ), and probabilistic neural networks (PNN) algorithms. Then, an ensemble classifier system is developed where the previous machines form the base classifiers, and support vector machines (SVM) are employed to aggregate decisions. The proposed approach leads to higher correct classification rates than the standard approach

[5], in this paper, scheme is proposed that non-negative and local non-negative matrix factorization (NMF, LNMF) are used to extract features from metabolite profiles. Then support vector machines (SVM) and linear discriminant analysis (LDA) are applied to train classifiers based on features extracted by NMF and LNMF. The new scheme can extract meaningful features and therefore obtains a classifier with good generalization. Experimental results show that the new method performs better than other previous ones. The proposed system gives the maximum accuracy for LNMF+LDA up to 96% and using LNMF+SVM, it gives 94%.

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[6] mainly focus on image mining, which is concerned with classifying brain tumors in MRI images. The steps involved in this system are: pre-processing, feature extraction, association rule mining, and classification. The pre-processing step has been done using the median filtering process, and features have been extracted using the texture feature extraction technique. The extracted features from the CT scan images are used to mine the association rules. In this system, we will use the Decision Tree classification algorithm. The proposed method improves the efficiency of traditional image mining methods. Here, results which get were compared with the Naive-Bayesian classification algorithm.

[7] propose a hybrid approach for the classification of brain tissues in magnetic resonance images (MRI) based on a genetic algorithm (GA) and support vector machine (SVM). A wavelet-based texture feature set is derived. The optimal texture features are extracted from normal and tumor regions using the spatial gray level dependence method (SGLDM). These features are given as input to the SVM classifier

[8] presented brain MRI classification by a fine-tuned transfer learning algorithm. The experiments were performed on pre-trained VGG16, AlexNet, and VGG19. VGG16 and AlexNet attained the average precision of 89.95% and 94.65%, respectively, for 5-fold cross-validation. VGG19 attained better performance than VGG16 and AlexNet. Wasule and Sonar [9] demonstrated the procedure for brain MRI classification.

III. SYSTEM BLOCK DIAGRAM

The MRI brain tumor detection is complicated task due to complexity and variance of tumors. In this approach, tumor is detected in brain MRI using thresholding technique and brain MRI classified into glioma, meningioma and no tumor using convolutional neural network.

In this approach, the clinical database of brain MRI is used. The database contains glioma, meningioma and no tumor MR images. The detailed distribution of the database is as shown in Table 3.1. The database contains raw images that are pre-processed, segmentation and augmentation technique after splitting training and testing data.

Table 3.1: Database Distribution

Type of MRI	Database Distribution		
	Total Images	Training Images	Testing Images
Glioma	370	250	120
Meningioma	370	250	120
No tumor	370	250	120

Preprocessing

The database images are raw, noisy and contain patient data text on the image. Firstly, the images are in the RGB color format. The RGB color is converted into grayscale using the weighted average method. Medical images mostly affected by Rician and salt & pepper noise. The median filter is effective in the presence of unipolar and bipolar impulse noise and salt and pepper noise [21].

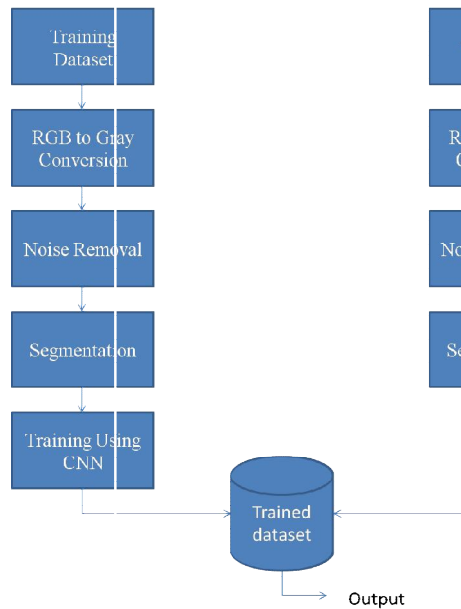


Fig.3.1 Flow diagram of the proposed system

PROPOSED SYSTEM

Overview:

1. Proposed system aims to provide an efficient and user-friendly approach to obesity classification by incorporating multiple machine learning algorithms. The system consists of three main modules: registration/login, training and testing dataset creation, and a camera module for real-time obesity detection.
2. Registration/Login Module:
3. Users register or log in, providing essential information such as name, gender, address, and email. This module ensures user identification and allows for personalized interactions.
4. Training and Testing Dataset Module:
5. This module focuses on creating a comprehensive dataset for training and testing machine learning models.
6. Features in the dataset include physical descriptors like age, height (in cm), weight (in kg), and BMI calculated from weight and height.
7. Camera Module:
8. The camera module captures full-body images of individuals in real-time.
9. Advanced machine learning algorithms, including SVM, DT, RF, and LR, analyze the captured images.
10. The algorithms perform pre-processing and feature extraction on the images, utilizing a logistic regression classifier for obesity classification.
11. Connection Between Modules:
12. The dataset created in the training and testing module serves as the foundation for machine learning model training.
13. This dataset includes a diverse set of features, allowing the models to learn patterns related to obesity from different perspectives.
14. The camera module utilizes the trained models to process real-time images and predict the obesity status of the individual.
15. User Input:
16. While the training dataset is initially populated with diverse data, user input can contribute additional information for a more personalized experience.
17. Users may provide their age and gender for the system to assess their obesity status based on the trained models.

Dataset Creation:

1. The dataset creation involves both user-provided information during registration and randomly generated data for diversity.

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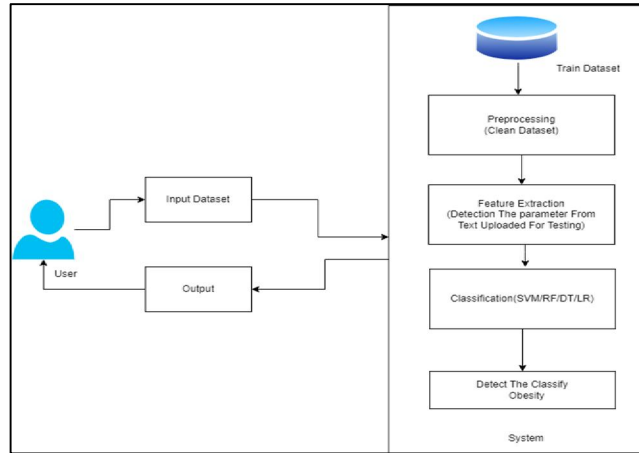


Fig: Proposed System Architecture

Used Algorithm:

Convolutional Neural Network (CNN)

CNN's are a category of Neural Networks that have proven very effective in areas such as image recognition and classification. CNN's are a type of feed-forward neural network made up of many layers. CNN's consist of filters or kernels or neurons that have learnable weights or parameters and biases. Each filter takes some inputs, performs convolution, and optionally follows it with a non-linearity[. A typical CNN architecture can be seen as shown in Fig.4. The structure of CNN contains Convolutional, pooling, Rectified Linear Unit (ReLU), and Fully Connected layers. CNN's are a category of Neural Networks that have proven very effective in areas such as image recognition and classification. CNN's are a type of feed-forward neural network made up of many layers. CNN's consist of filters or kernels or neurons that have learnable weights or parameters and biases. Each filter takes some inputs, performs convolution, and optionally follows it with a non-linearity[. A typical CNN architecture can be seen as shown in Fig.3.2. The structure of CNN contains Convolutional, pooling, Rectified Linear Unit (ReLU), and Fully Connected layers.

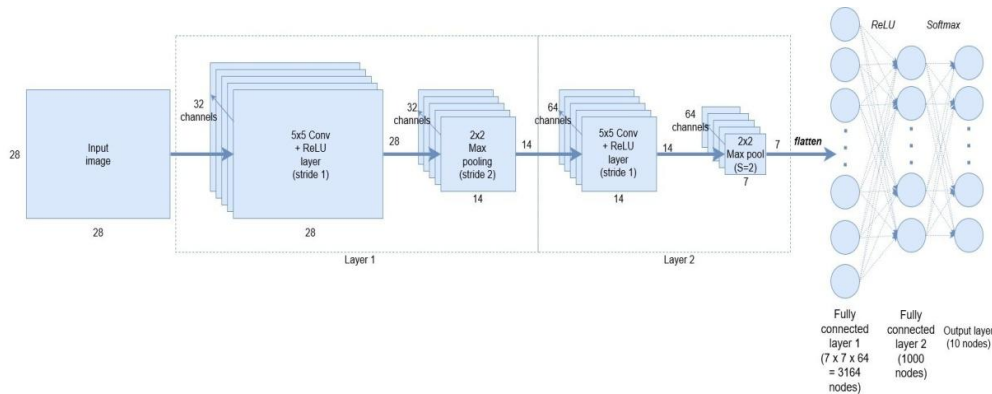
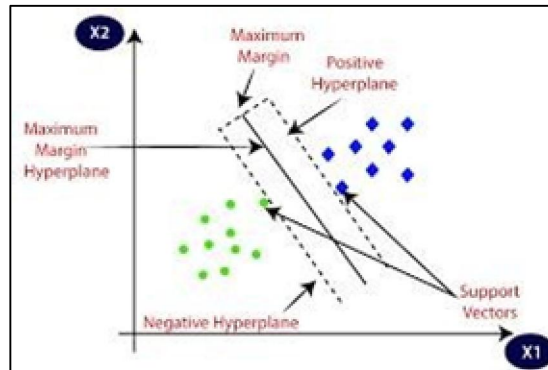


Fig 3.2 Architecture of CNN

Support Vector Machine(SVM):

Support Vector Machine is a supervised learning algorithm used for classification and regression tasks. It works by finding the optimal hyperplane that maximally separates different classes in the feature space. SVM is effective in high-dimensional spaces and is particularly useful when clear boundaries between classes exist..



(4.3.1 Fig.SVM)

Decision Tree (DT):

Decision Trees are tree-like structures that recursively split the dataset based on features to make decisions. They ask a series of questions to divide the data into subsets, ultimately reaching a leaf node with a final decision. Decision Trees are intuitive, easy to understand, and suitable for both classification and regression problems.

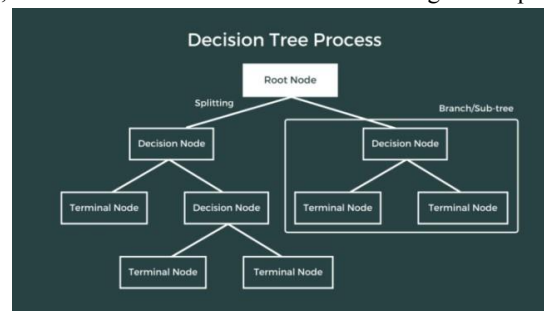


Fig: Decision Tree

Random Forest (RF):

Random Forest is an ensemble learning method that constructs multiple decision trees during training and merges their predictions for more accurate and robust results. By combining predictions from diverse trees, Random Forest reduces over-fitting and improves generalization, making it a powerful tool for classification tasks.

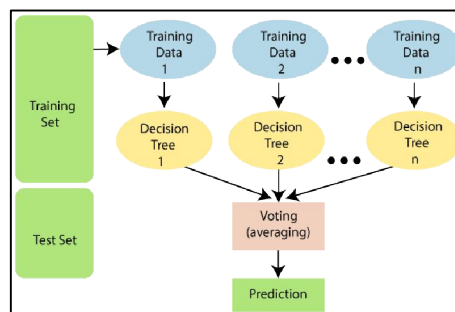


Fig: Random Forest

Logistic Regression (LR):

Logistic Regression is a statistical technique used for binary classification, predicting outcomes like yes/no or true/false. It models the relationship between input features and a binary target variable by estimating the probability of the positive class. The logistic function maps the output to a probability range (0 to 1). It's commonly applied in diverse fields for tasks involving binary decisions

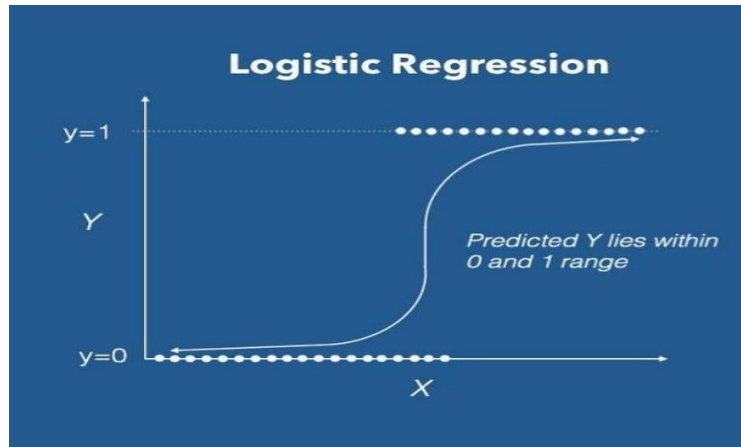


Fig. Logistic Regression

IV. TECHNOLOGY USED

Python

Python is featured with a dynamic type system, automatic memory management and supports multiple programming paradigms, including object-oriented, imperative, functional programming, and procedural styles. It has a large and comprehensive standard library. Python is an interpreter, object-oriented, high-level programming language with dynamic semantics. Its high-level built-in data structures, combined with dynamic typing and dynamic binding, make it very attractive for Rapid Application Development.

Spyder

Spyder is a powerful environment build in Python, for Python, and designed by and for scientists, engineers, and data analysts. It offers a unique amalgamation of the advanced editing, analysis, debugging, and profiling functionality of a wide-ranging development tool with the data study, interactive implementation, deep examination, and beautiful visualization capabilities of a scientific package.

Anaconda

Anaconda is a freemium open-source distribution of the Python and R programming languages for large-scale data processing, predictive analytics, and scientific computing, that aims to simplify package management and deployment. Package versions are managed by the package management system conda.

Anaconda is widely favored by data scientists and researchers for its simplicity, extensive library support, and ease of use in setting up Python and R environments for various data-related tasks.

Image processing Library: OpenCV 3.6

OpenCV (Free Open Source Computer Vision) is a library of programming functions mainly aimed at real-time computer vision. It has a BSD license (free for commercial or research use). OpenCV was originally written in C but now has a full C++ interface and all new development is in C++. There is also a full Python interface to the library.

Tensorflow

TensorFlow is an end-to-end open-source environment for ML. TensorFlow is a wealthy system to handle all aspects of the ML system. However, this class focuses on using a particular TensorFlow API to develop and train ML models.

TensorFlow APIs are set hierarchically. ML researchers use low-level APIs to create and explore new ML algorithms. In this class, you will use a high-level API named `tf.keras` to define and train ML models and to make predictions. `tf.keras` is the TensorFlow variant of the open-source Keras API.

Keras

Keras is an open-source NN library written in Python. It can be executed on top of Tensorflow Microsoft Cognitive Toolkit, R-language, Theano, or PlaidML. It is developed to enable superior experimentation with DNN, it focuses on being user friendly, modular, and extensible. It was developed as part of the study effort of project ONEIROS, and its primary author and maintainer are Francois Chollet, a Google engineer. human beings, not machines", and "follows best practices for reducing cognitive load".

- Keras was created to be user-friendly, modular, simple to enlarge, and to work with Python. The API was "designed for PythonLibraries
- Tkinter
- Numpy
- Matplotlib
- Keras
- Pandas
- PyTorch
- Pillow
- OpenCV
- TensorFlow

V. CONCLUSION

In brain tumor detection we have studied about feature based existing work. In feature based we have study about image processing techniques likes image pre-processing, image segmentation, features extraction, classification. And also study about deep learning techniques CNN and VGG16. In this system we have detect the tumor is present or not if the tumour is present then model return's yes otherwise it return no. and we have compared CNN with the VGG 16 Model. The result of comparison VGG 16 is more accurate than CNN. However, not every task is said to be perfect in this development field even more improvement may be possible in this application. I have learned so many things and gained a lot of knowledge about development field

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