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BRAIN TUMOUR DETECTION OF MRI IMAGES USING MACHINE VISION TECHNIQUES

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Article Info

Abstract

Brain Tumour MRI detection is a challenging task for a doctor. Early detection of a brain tumour disease is a very good for brain tumour patient for the recovery of brain disease. Machine vision techniques are becoming so popular now a days in brain tumour detection. In this research image processing methodology is used for the enhancement of images of brain tumour and clearly detection of MRI images. CVIP tool is also important part of this research the primary purpose of the CVIP tools development environment is to enable students, teachers, researchers, and all users to explore the power of digital image processing. In this research CVIP tool used for image pre-processing, feature extraction, and classifications for result. Through this the results for classification of brain tumour images give better understanding and better results. Different classifiers are used that include Naive Bayes with accuracy 90%, BOVM based SVM with accuracy 97.3% and CNN with accuracy is 98.5%. So, this Accuracies shows that CNN gives a better accuracy with 98.5% than other classifiers.

Keywords: *Deep Learning, Brain Tumour, Classification, SVP, Machine Vision*

Introduction

The condition of brain tumours affects many people each year. The formation of aberrant cells leads to tumours. Brain tumours can either be benign or malignant (cancerous). Moreover, can be further broken down into primary and secondary categories. Primary tumours start in the central nervous system, as opposed to secondary tumours, which originate from locations outside the brain. Based on the anomalies in the tissue of the brain, tumours are categorized into one of four groups. Grades 1 and 2 tumours are considered low-risk. Due to their prevalence, tumours with a grade of 3 or 4 are particularly susceptible to malignancy. Meningiomas, which develop towards the top and outer curve of the brain and comprise 36.1 percent of all primary tumours, the most typical primary tumour kind. Meningiomas are a type of slow-growing, non-cancerous tumour that can impair vision. Gliomas are abnormal growths of the glial cells that protect neurons in the human brain. Pituitary tumours may negatively affect how the body functions. Meningiomas can be classified as benign tumours or malignant tumours based on the anatomical location, form, and cell makeup of the tumour. A pituitary tumour is an abnormal growth of the cells that surround the surface of the pituitary gland. Primary brain tumours are extremely challenging to detect in the early stages due to their location, form, and variability. In non-invasive imaging treatments, tissues' absorption qualities are exploited. genuinely imaging tumours demands a precise description of the absorption rate. The three tumour types examined in this case study are interchangeable in terms of absorption (Pixel grey level). Tumour form will therefore be a challenging factor to use in classifying them. Deep learning has recently become quite important in the domains of pattern recognition and shape recognition. Transfer learning allowed Deep Learning to eliminate the time-consuming step of starting from scratch while training models. Transfer learning was used since Resnet 50 was pre-trained using an ImageNet database that contained more than 1000 different target classes. It was suitable for identifying brain tumours thanks to discriminative learning % with Grab Cut and Skull stripping during pre-processing, allowing the final layers to only be trained on MRI data while keeping the core pattern recognition from the Resnet50 by using pre-learned %.

1.1 Brain cancer

The brain is a crucial organ in the human body that manages and makes decisions. The nervous system's defence begins here since it functions as the brain's instruction and control centre. Atypical cells damage the brain and are the main factor in most tumours. Meningioma, glioma, and pituitary tumours all have their origins in the brain, in contrast to other types of cancer. The thin membranes of the brain are where meningiomas, a non-cancerous tumour form, are most frequently found. One of the worst disorders that can harm a person's crucial life is a brain tumour. It is challenging to visualise all of the different phases of a brain tumour if one hopes to avoid or treat the disease. As a result, radiologists frequently employ Magnetic Resonance Imaging (MRI) to check for brain tumours. The outcome of this test indicates the state of the brain's health. On the other hand, if anomalies are present, it may be possible to determine the type of tumour. With the advent of machine learning, it is crucial to analyse MR images for accurate and speedy brain cancer detection.

1.2 Feature extraction and machine vision

The actual three elements of the technique were feature creation, data collection and division, and MR image pre-processing. The median filter was used at the pre-processing stage to improve picture quality and preserve the edges. After pictures have been segmented, it is feasible to extract relevant attributes from them using techniques like k-means, fuzzy C-means, and others. Segmenting images is necessary for image analysis and interpretation. Only a few of the numerous applications for this technology in brain imaging include matching, blood cell delineation, and surgical planning. For segmentation, 3D MR images of a brain tumour are split up using a CNN. The anatomical makeup of the brain is automatically recognized using a deep neural network-based technique. It is possible to employ a combination of discrete Gaussian patterns and higher-order patterns like Markov-Gibbs to display on a group of appearances, like intensity form modes. An attempt is made to develop a deep auto-encoder hybrid based on Bayesian fuzzy clustering. After applying a non-local mean filter, brain tumours are segmented using a Bayesian fuzzy clustering approach. The left and right halves of the 2D MRI images are separated, and statistical properties like mean, homogeneity, absolute value, and inertia are attempted in order to train the Support Vector Machine (SVM) classifier. Due to the huge number of features in step two, most research involves a second step to extract features with more valuable information utilizing techniques like PCA, SIFT detectors, and SURF descriptors.

After a hybrid feature extraction by a covariance matrix, a regularized extreme learning method is used to identify any anomalies in the brain. To choose from a fusion of features, particle swarm optimization (PSO) and other evolutionary methodologies are also applied. The most significant machine learning techniques for classifying images include K-nearest neighbors, decision trees, support vector machines (SVM), Naive Bayes classification approaches, maximizing, and random forests. Based on characteristics extracted in feature extraction, fNIRS and EEG brain-computer interfaces are classified using SVM and Linear Discriminant Analysis (LDA) (LDA). Convolutional Neural Networks (CNN) are now widely employed in a number of applications, such as video analysis and the analysis of medical images. CNN needs to be able to recognize the most crucial patterns and details in training images in order to be effective. For medical images like the identification of brain disorders, popular image classification architectures like VGGNet, GoogleNet, and AlexNet are commonly taken into consideration. Investigations are being conducted on the pre-processing and preparation of data using 3D filters and CNNs with multi-path and cascade topologies. Many emotions and directions can be added to a person's portrait using a pixel CNN architecture. A succession of cascaded convolutional neural networks are used to iteratively create a room's decor (CNNs). Because of this, scientists are striving to create new, simple-to-compute models that are just as good at classifying tumours as CNN. One frequent tactic is to think of a number of small collaborative learners rather than a difficult network for quick training and resemblance. These peer networks have the potential to develop independently or to rely on one another. Estimating the distribution of the data is one of the most frequent jobs in machine learning. Without prior knowledge of the hard-coded correlations, it is challenging, for instance, to discern relationships between adjacent picture pixels. The data-driven predictor auto-regressive models reject these connections in general datasets. Based on either noisy or insufficient data, these models provide superior images. An adequate density estimator is likely to resolve classification, regression, missing data, and related problems.

1. Related work

The researchers used a pre-trained CNN as a starting point for this study. Because the datasets in medical analysis are typically limited, transfer learning will be extremely useful. In order to fine-tune the system, they used transfer learning. Fine-tuning occurs in the VGG's last block, which is separate from the other blocks, which stay frozen. If the final two blocks need to be fine-tuned, all prior levels will be locked. The proposed approach was tested on a benchmark dataset of 3064 T1-weighted MRI images. Five-fold cross validation yielded a 94.42 percent accuracy rate. Our technique was fine-tuned using discriminative learning rather than transfer learning. It was utilised to keep the weights of the early layers stable using the tilted triangle learning rate distribution, which is better at recognising basic features than a linear learning rate distribution.

It is in this chapter that we review the various ways we've used to proving our theory. Because they are all of the same type but of varying degrees of severity, segmentation was used to construct masks for tumour identification. There were too many different types of cancer to adopt this method. Techniques to remove noise from MRI images were used by Begum et al. We didn't apply any further noise reduction measures because we were undertaking skull stripping, which involves morphological processes. The grab cut approach uses two CNNs and a join distribution to segment an image, whereas the Hashem et al method uses GMMs to extract the foreground and background pixels in a picture. This project's performance was improved with the help of a block-based hyperparameter tuning technique. Discriminative learning rates were used instead of altering hyperparameters.

Machine learning is used to detect brain tumours using techniques such as active contour segmentation, level set and changes algorithms, pre-processing, and thresholding. In the pre-processing stage, remove the skull and denoise it. The Harvard database was used to obtain the T 1w MRI benchmark dataset. 256 × 256 is used in Matlab 2020's core I 6 system for evaluation. In terms of energy efficiency, the cv global strategy is preferable to the level set approach. In the future, advances in machine learning should lead to increased accuracy and speed in computations.[1]

It is possible to detect brain tumours using machine vision. SVM, K means clustering method, and median filter are some examples of algorithms that can be used to analyse data. The BRATS 2015 Benchmark dataset is used for this. RGB to Gray Scale conversion introduces artefacts, which can be minimised by pre-processing. These strategies are more effective.[2]

When a brain tumour is discovered, it is a long and difficult road ahead. Convolutional neural networks can be used to create one model using two convolutional layers and a max-pooling kernel with 2d-stride length. Scale feature extraction is followed by feature concatenation as part of the data pre-processing. It is necessary to perform pre-processing steps such as skull removal and pixel standard deviation prior to entering a CNN. Kernels (big, medium, and small) are utilised in the feature extraction process. There were 233 patients with brain tumours who had their T1-CE MRI scans used to find them. Validation with 5-fold cross-validation indices yielded an accuracy of 0.973 percent. FCN (fully convolutional neural network) architecture will be compared to our proposed model in the future. Using the proposed multiscale convolutional neural network, satellite images might be analysed.[3]

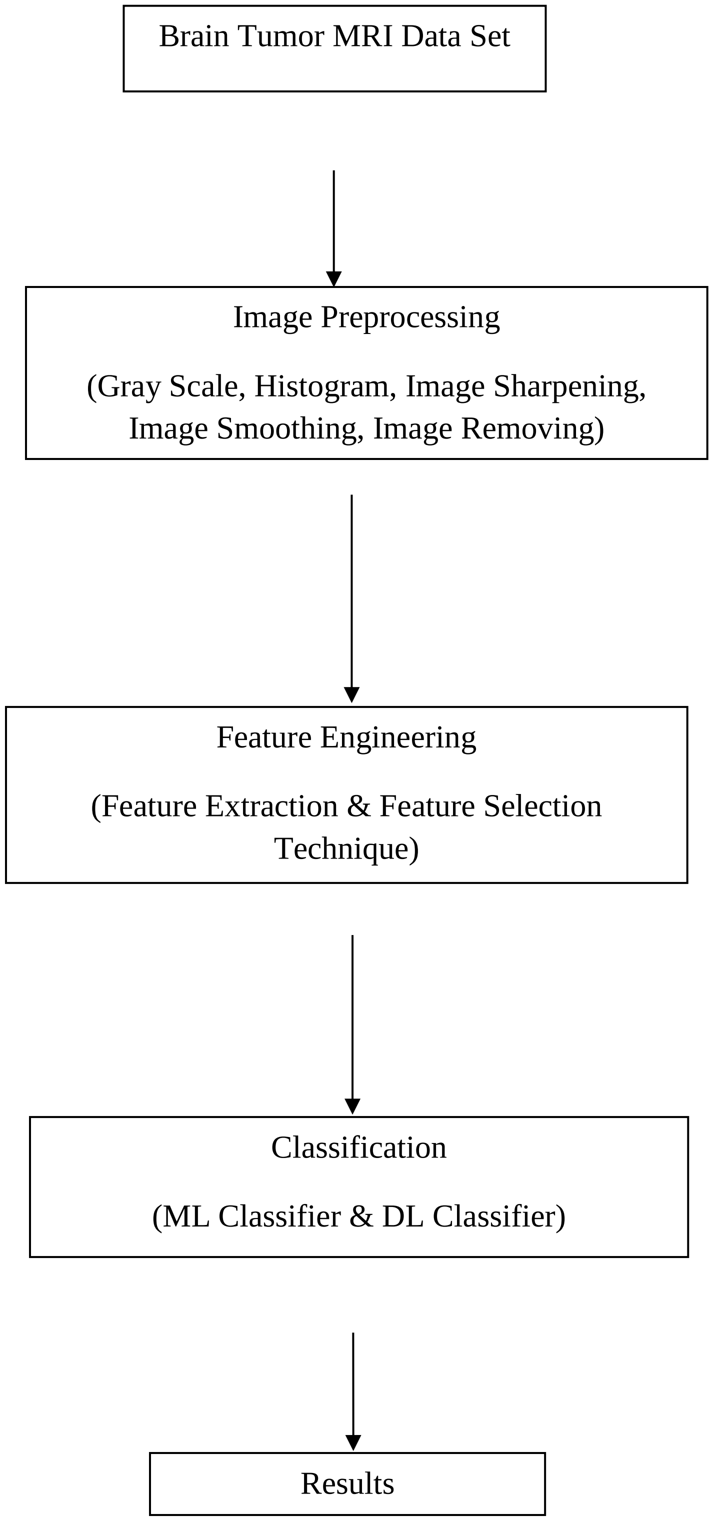
This is a machine that can detect brain tumours. Transfer Learning (Gaussian naive bayes and AdaBoost), K-Nearest Neighbours, Random Forest and Support Vector Machine are only few of the techniques featured in this class. Pre-processing techniques include extreme point computations, MR image thresholding, noise reduction by dilation and erosion, and image augmentation. Three datasets are used for deep CNN feature extraction, training, and optimization: BT-small-2c, a small dataset with two classes (normal/tumour), BT-large-2c, a huge dataset with two classes (normal/tumour), and BT-large-3c, an enormous dataset with four classes (normal/tumour) (normal, glioma tumour, meningioma tumour, and pituitary tumour). Classification is done using all three datasets in a Deep CNN. Your results will vary depending on the options that you choose. To find the classifier with the lowest standard deviation, compare nine different ML classifiers (including the Gaussian NB and AdaBoost classifiers). Then, select the classifier with the lowest standard deviation. Select the next most accurate characteristic following this step. There is a lack of variation in the feature set. An ensemble of the DenseNet-169, Inception V3, and ResNext-50 deep features is best used for MRI datasets that have more than two classes of normal and cancerous tissue (e.g., three or more tumours). An ideal combination of DenseNet-169, ShuffleNet V2, and MnaNet deep features was discovered. (Normal, glioma tumour, meningioma tumour, and pituitary tumour). Using knowledge distillation methods, it will be possible to reduce the model's size for use in a real-time medical diagnosis system [4]. An accurate model for the detection of brain tumours was developed using T1-weighted data, a Chan–Vese neural network, and a convolutional neural network. Collections from Guangzhou and Tianjing Medical University General Hospitals are included in this collection for the years 2005 to 2010. Every detail has been meticulously planned. In order to reduce the network's complexity, five rounds of cross-validation lower the output sensitivity by a sliver. Thus, training and testing may now be done in half the time. Dice scores of 0.92 (accuracy), 0.9457 (RI), 0.9936 (VOI), 0.301 (GCE), 0.004 (BDE), and PSNR of 77.076 were achieved by minimising weighted parameters (PSNR). To categorise and segment brain tumours, this approach can be used even in low-resource and knowledge environments in the future. An article titled "An MRI Brain Tumour Localization and Segmentation Systematic Approach Using Deep Learning and Active Contouring" was published in the Journal of Healthcare Engineering in 2021. (2021).[5]

The MRI scan data were normalised and improved in contrast via preprocessing.

The covariance matrix was developed by extracting features from the brain tumour classification model in order to improve its accuracy. After a 10-fold cross validation, the proposed model was shown to be 99.25 percent accurate. A proposed differential deep-CNN model can automatically classify brain tumours, according to this study. The overall success of our deep-CNN differential model will be evaluated in the future. Rapidly expanding coverage can be achieved by altering the differential filter's settings. Adding a multi-channel classifier to deep network topologies can increase classification performance.[6] Tumours of the brain can be deadly. For an algorithm, use this model of a major sickness. A back-propagation training algorithm and multithreading training model are also included in convolutional neural networks. Getting the information ready for analysis A high degree of modularity should be ensured in the design of the individual components. The CLM model was shown to be 96 percent accurate in this study, with a precision/recall ratio of roughly 95 percent for each of its predictions. In the future, focus your efforts on improving CNN's abilities. The utilisation of a high number of threads is an additional option to consider. Special filter weights on CNN layers can be used to create more accurate feature maps that include more information about an image's principal parts.[7]. A brain tumour has the potential to kill. On your own, it's really tough to identify this issue. Random forest classifiers, the Kneighbors classifier, support vector machines, and logistic regression are some of the models that can be used to diagnose tumours. Multidimensional, univariate, and bidimensional selection methods were used to narrow the field of potential candidates. An analysis of Kaggle.com data shows that when used to identify brain tumours, xception was 88.1 percent accurate, conception 3 was 92.7 percent reliable, and CNN was 90.67 percent reliable. Every single one of the outcomes was within ten per cent of the actual value under these conditions. In the future, it is possible that various types of brain tumours may be classified.[8].

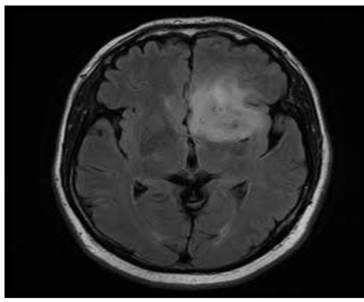
2. Proposed Methodology

In this section methodology is discussing that consists on collecting brain tumour MRI dataset, Image preprocessing, Feature Engineering, classification and results. A below diagram represents complete methodology in detail with clear concept.

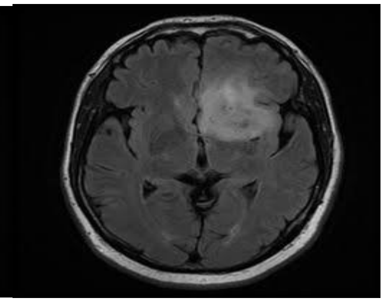


2.1.Brain Tumour MRI Data set

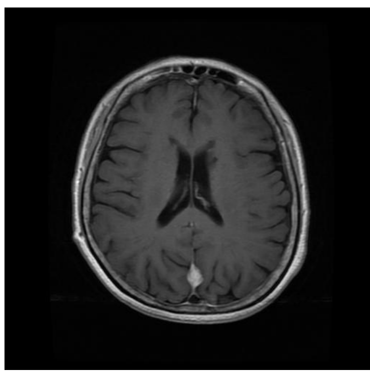
In this research work brain tumour data set is collected from online sources and different sites.MRI data set consists on 288 images.In this work four classes of brain collected Glioma contains 72 images, Meningioma contains 72 images, Pituitory contains 72 images and Non tumour also contains 72 images. Glioma is a type of brain tumour that occurred in human brain when gilal cells become out of control it also occured in spinal cord and support nervous system. Every year approximately 80000 people effected with brain tumour in which 25% of people effected with glioma. Meningioma is also a type of brain tumour that begins in the spinal cord or brain. Meningioma consists on three grades grade 1 is low grade tumour , grade 2 is mid grade tumour, grade 3 is high grade tumour most malignant and fastest growing tumour. Pituitory is also a type of tumour that are abnormal growths and occurs in pituitary gland. It also effected your important and main parts of body. It produce a symptoms such as headache and vision loss.



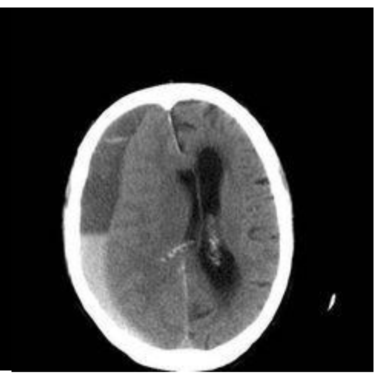
Glioma



Meningioma



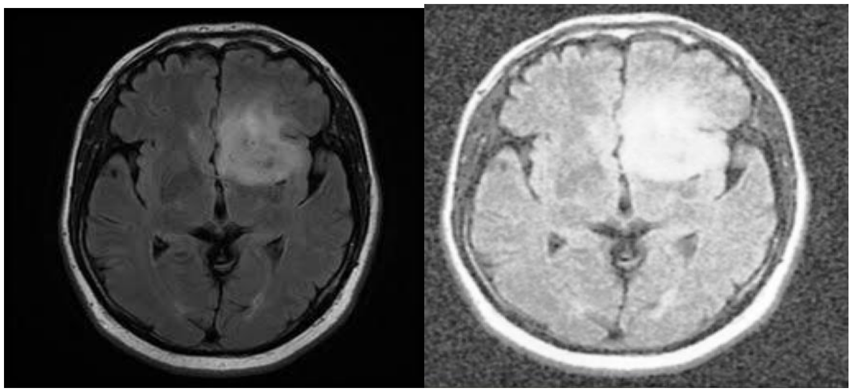
Pituitary



NO Tumour

2.2. Image Processing

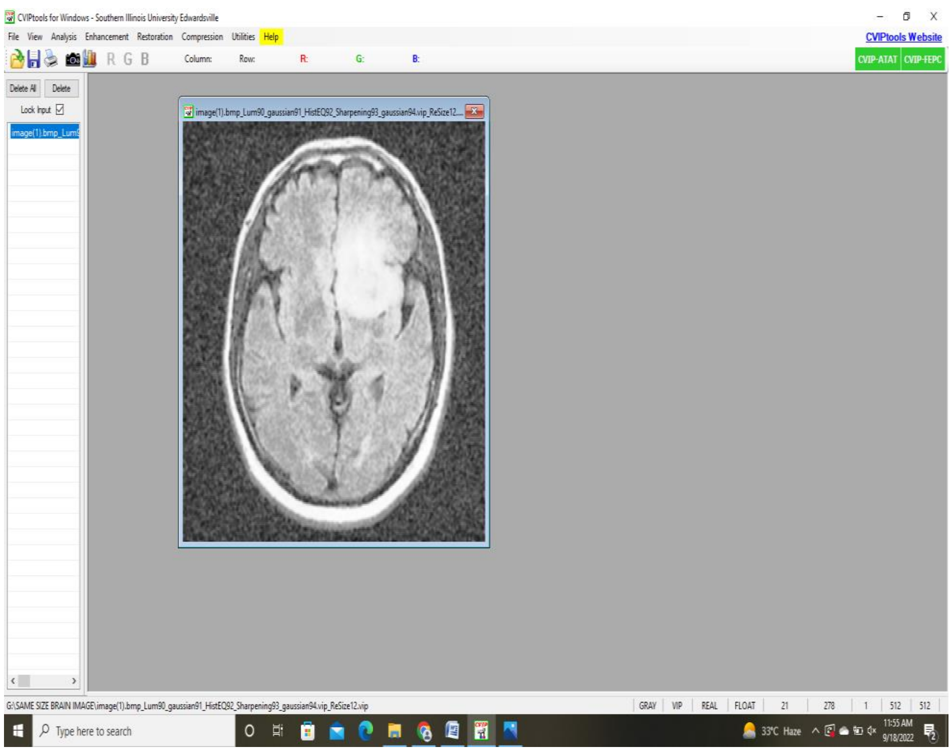
Image processing is a method for performing some operations on an image to obtain an improved image or to extract some useful information from it. It is a type of signal processing in which the input is an image and the output can be an image or characteristics/properties associated with that image. Nowadays, image processing is one of the rapidly developing technologies. It forms a major research area within engineering and computer science disciplines. Image pre-processing include a step that perform before modeling for enhance and format an image. Steps include Gray scale conversion, Noise removing is step that reduce and remove the visibility of noise, Histogram Equalization is used to improve the contrast of images, Sharpening used for feature extraction in images and Smoothing removing image perturbations, these steps are performed by CVIP tool on 288 images by using above mentioned steps. Images before pre-processing and after pre-processing are shown below.



Before Pre-processing **After Pre-processing**

2.3. CVIP Tool

The main goal of the CVIPtools development environment is to make it possible for users to explore the potential of digital image processing, including students, teachers, researchers, and other users. The original CVIP utility is a feature-rich GUI-based programme that incorporates algorithms for image analysis, enhancement, restoration, and compression. It contains CVIP-ATAT for the creation and analysis of algorithms and CVIP-FEPC for the conduct of experiments using sizable groups of images and various feature extraction and pattern classification parameter combinations. A simple software that gives users access to the entire functionality of the CVIP tool package is called CVIP Lab for C/C++ programmers. The most recent addition is the CVIP Toolbox for MATLAB, which includes copies of the CVIPtool library functions for Matlab as well as a skeleton of the CVIPlab programme for exploring the Toolbox.



2.4. Feature Engineering

Feature engineering is a step that includes feature extraction and feature selection. Raw data are converted to numerical representation during feature extraction. It demonstrates an improved end result and increased accuracy of an image employed in this research issue. The amount of redundant data in the chosen data set is decreased by feature extraction. It also creates the model quickly and accurately with minimal machine effort. In order to categorise photos, feature extraction uses an object-based technique in which each object (also known as a segment) is a collection of pixels with comparable spectral, spatial, and/or textural qualities. The spectral data included in each pixel is utilised to categorise photos using traditional pixel-based classification techniques. The object-based method provides more flexibility in the kinds of features that can be recovered from high-resolution panchromatic or multispectral imagery.Calculation of various attributes for segments

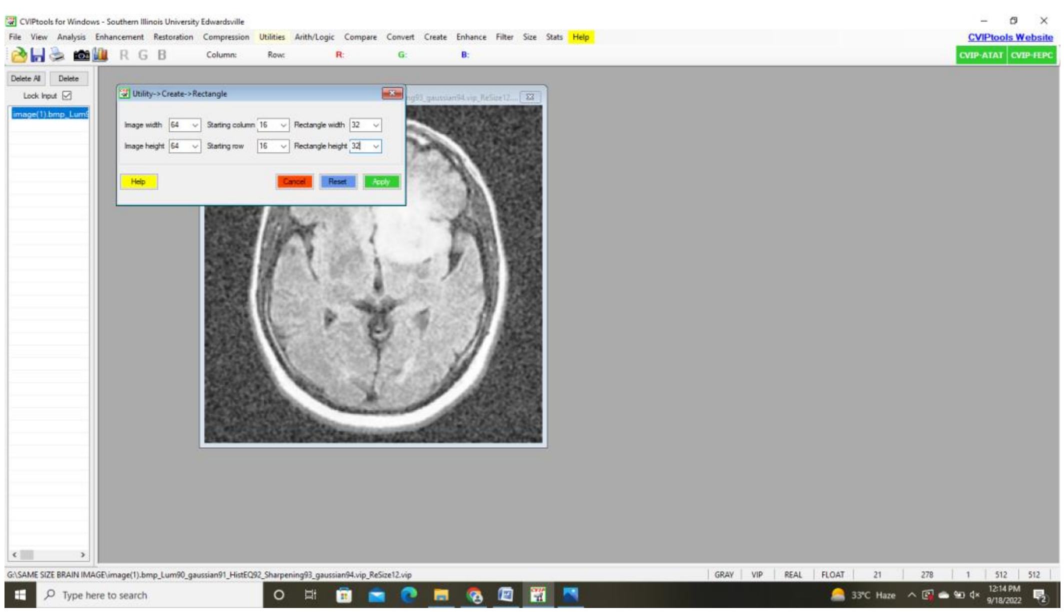
- Creating several new classes
- Interactive assignment of segments (so-called training samples) to each class
- Whole image classification using K Nearest Neighbor (KNN), Support Vector Machine (SVM) or Principal Component Analysis (PCA) supervised classification method based on your training samples.
- Export classes to a shapefile or classification image.

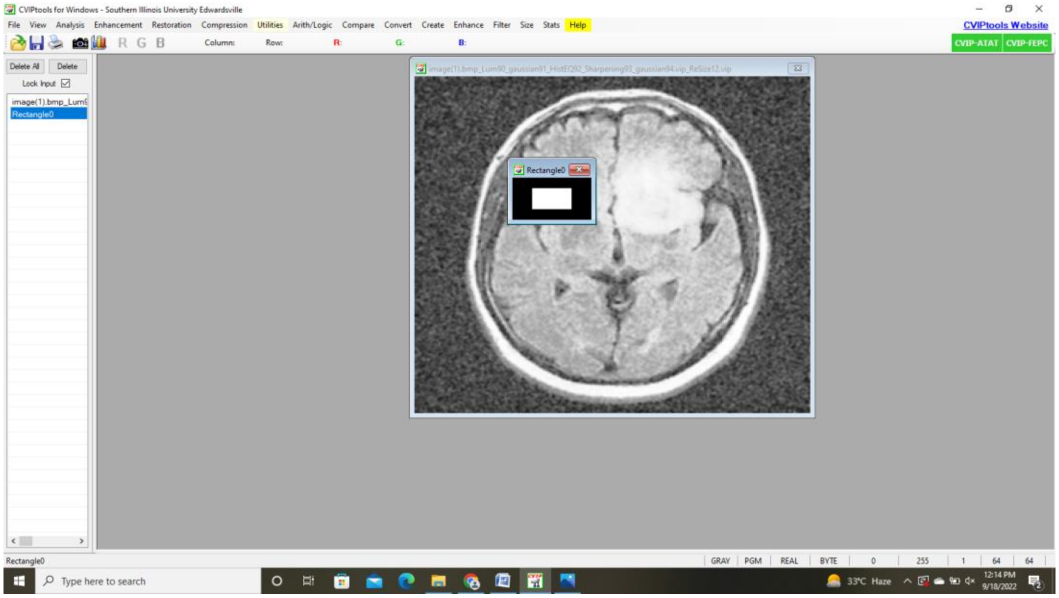
2.5.Feature selection

By using only pertinent data to eliminate noise in the data, feature selection is a technique for lowering the number of input variables into a model. According on the kind of issue you are attempting to resolve, this is the process of automatically choosing relevant characteristics for your machine learning model.

2.6.In this thesis Feature engineering and results performed by CVIP tool.

Select image make a rectangle of image width, height 64, image column, row 16 and rectangle width, height changes every region of interest on every image such as 32,34,36,38 then place the rectangle four different angles(places) of images for taking the feature results from selecting original image rectangle and segmented image was pre-processing image and given a file name and selected four options binary features histogram feature, Texture feature.



3. 
CVIPtools for Windows - Southern Illinois University Edwardsville
File View Analysis Enhancement Restoration Compression Utilities Arith/Logic Compare Convert Create Enhance Filter Size Stats Help
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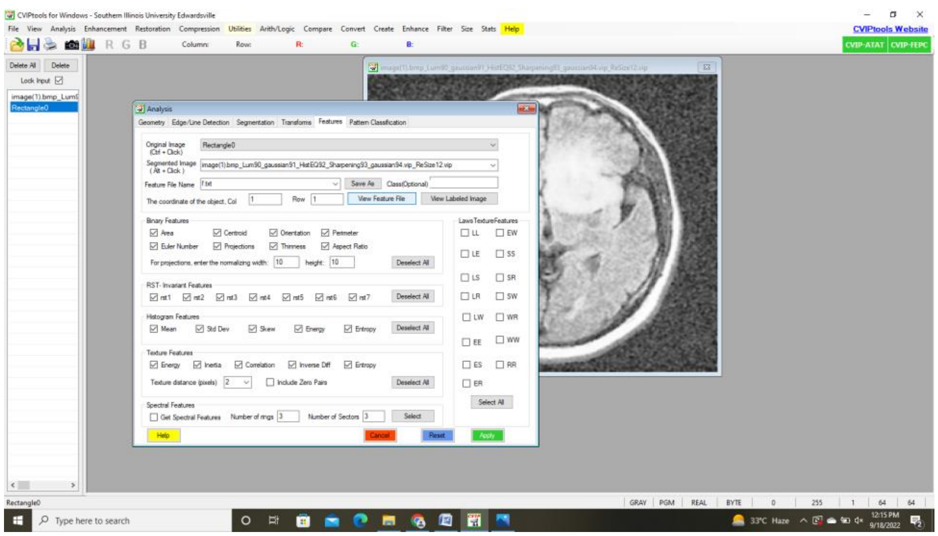
CVIPtools for Windows - Southern Illinois University Edwardsville
Analysis
Geometry Edge/Line Detection Segmentation Transforms Features Pattern Classification
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RST- Invariant Features
Histogram Features
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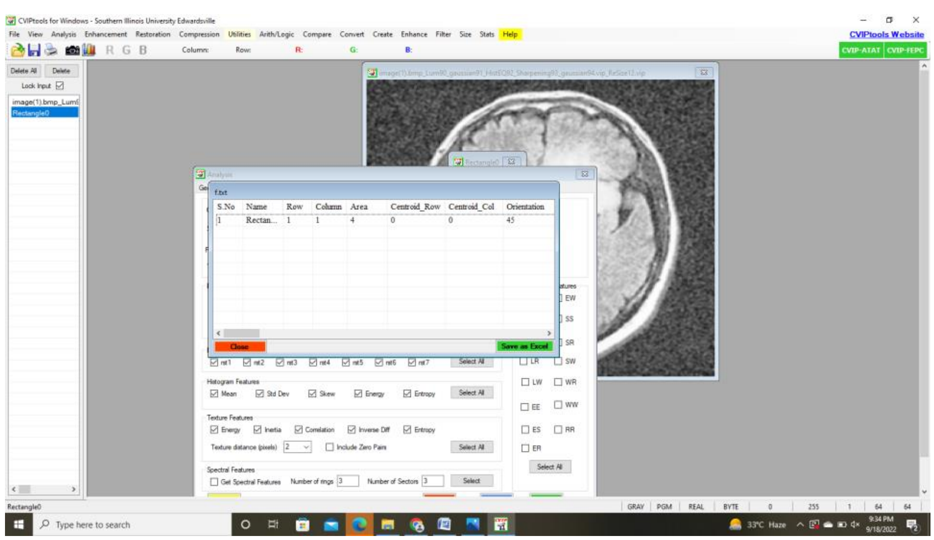
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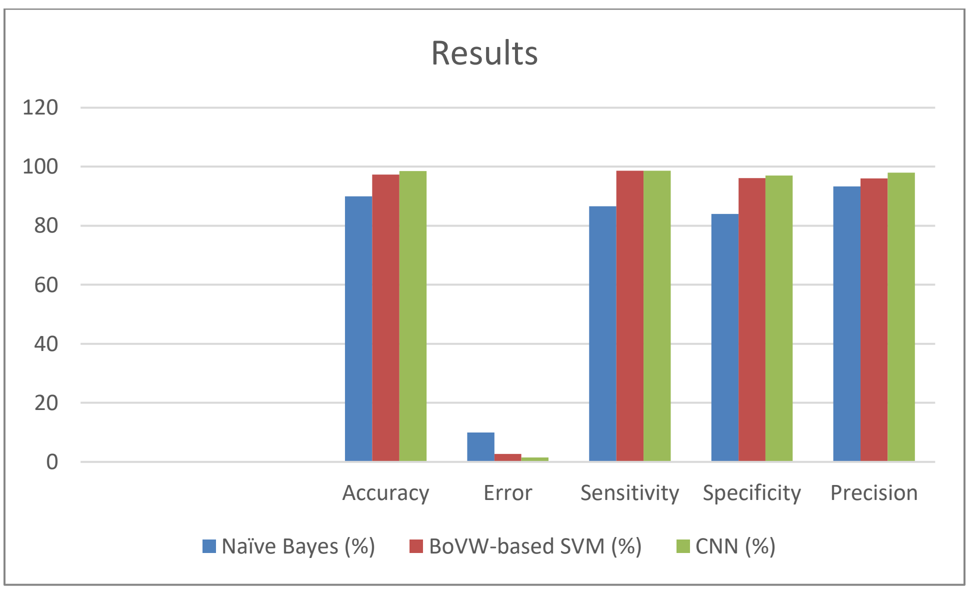
After this apply different classifier Naive Bayes, BOVM based SVM, CNN, RF, DNN for getting a better result that discussed in section 4.

4. Results and Evaluation

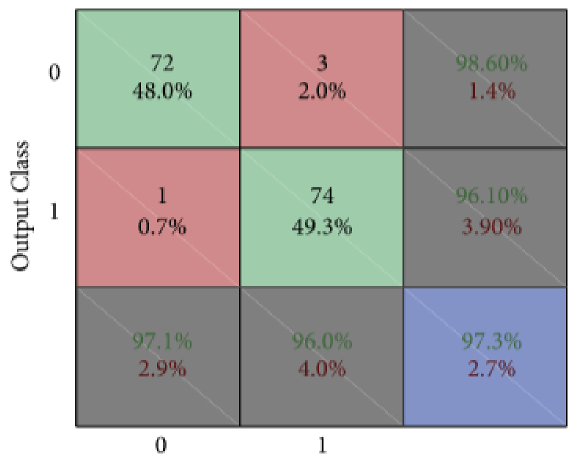
This section shows the results that obtain by a system Core i7, 64 bit operating system , Ram 4gb ,Cvip tool , and different classifiers are used for getting a good results,First perform preproceesing on data set of 288 same size images then performs a feature extraction with cvip tool then perform classification with different classifiers.Different Classifiers are used in this thesis that include Naive Bayes , BOVM based SVM , CNN, RF , SVM , DNN . Accuracy of Naive Bayes is 90% with error 10%, accuracy of BOVM based SVM is 97.3% with error 2.7% , Accuracy of CNN is 98.5% with error 1.5%, Accuracy of RF is 0.9955% , Accuracy of SVM is 0.978% and Accuracy of DNN is 0.9813%. Sensitivity of Naive Byes is 86.6%, BOVM is 98.6% , CNN is 98.6% RF is 0.9986% , SVM is 0.9970% , DNN is 0.9955% , Specificity of Naive Bayes 84% , BOVM based SVM is 96.1% , CNN is 97% , RF is 0,9947 %, SVM is 0.9742%, DNN is 0.9778 % , and precision of Naive Bayes is 93.3%, BOVM based SVM is 96% , CNN is 98%. This percentage of results are shown in table below.

Classifier	Naïve Bayes (%)	BoVW-based SVM (%)	CNN (%)
Accuracy	90	97.3	98.5
Error	10	2.7	1.5
Sensitivity	86.6	98.6	98.6
Specificity	84	96.1	97
Precision	93.3	96	98

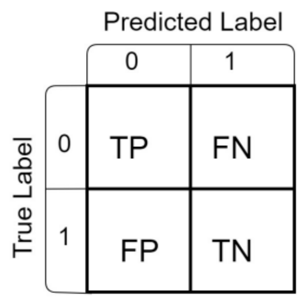
Graphically representation



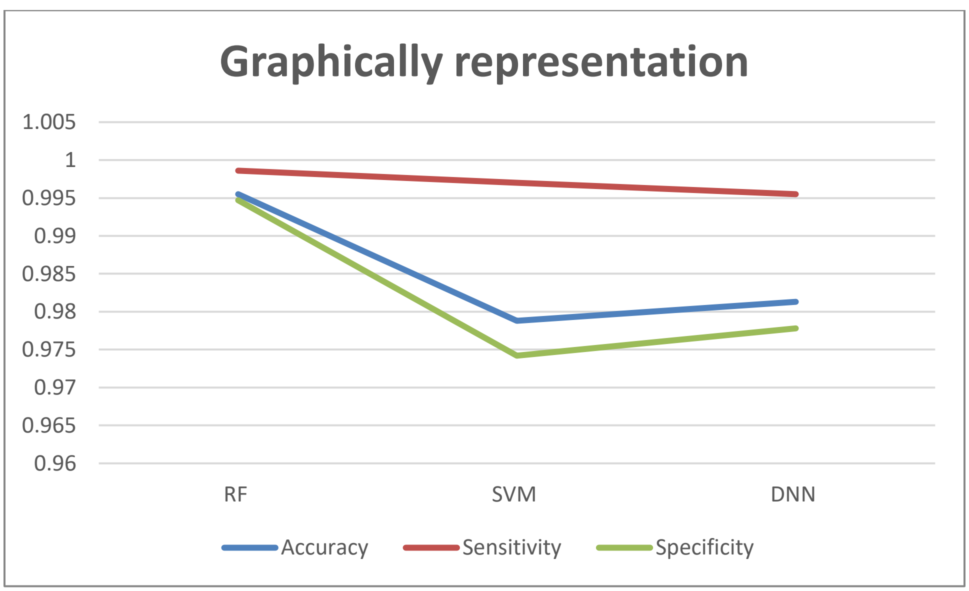
The confusion matrix of Naive Bayes shown below with percentage of results.



The above information can be predicted as



Classifier	Accuracy	Sensitivity	Specificity
RF	0.9955	0.9986	0.9947
SVM	0.9788	0.9970	0.9742
DNN	0.9813	0.9955	0.9778



The binary classifiers AC, SN, and SP noted in the confusion matrix are defined as follows: 1. Accuracy (AC): AC is determined by dividing the total range of all accurate predictions by the total range of datasets. the sum of TN and TP price is the range of all accurate predictions, hence the formula for AC may be written as

$$AC = \frac{TP+TN}{TP+TN+FN+FP} = \frac{TP+TN}{P+N}$$

All positive values are denoted by P, and all negative values are denoted by N. The acceptable value for AC is 1, while the worst cost price is zero. 2. Sensitivity (SN): The ratio of the total number of accurate, high-quality predictions to the total number of nice is used to determine SN. SN is occasionally also referred to as recall or true positive rate (TPR). SN can be formulated as:

$$SN = \frac{TP}{TP+FN} = \frac{TP}{P}$$

SP is calculated as ratio of a total number of correct negative predictions to a total number of negatives. It is referred to as True Negative Rate (TNR), and the formula are for calculation is:

$$SP = \frac{TN}{TN+FP} = \frac{TN}{N}$$

Dice similarity index and can be expressed as:

$$DSC = \frac{2|X \cap Y|}{|X| + |Y|}$$

Also

$$DSC = \frac{2TP}{2TP+FP+FN}$$

51

A type of error dimension known as VOE is typically stated as a percentage. VOE is determined as the union of the anticipated segmented region and the reference segmented vicinity divided by the intersection point or vicinity. As the complement of the Jaccard coefficient, VOE can also be calculated. The formula for the Jaccard coefficient (J) and VOE

$$J = \frac{|G \cap P|}{|G \cup P|}$$

$$VOE(G,P) = (1-J) * 100\%$$

is:

In this G represents the ground truth for object and p refers to predicted and segmented object.RAVID stands for Relative Absolute Volume Difference it can be calculated as

$$RAVD = 100\% * \frac{|P| - |G|}{|G|}$$

ASD stands for Average Symetric Surface Distance it can expressed as

$$d(v, S(G)) = \min_{s_g \epsilon S(G)} ||v - s_g||$$

5. Conclusion

Brain tumour detection of human brain is a challenging task in medical field this is a serious task for patient.Doctors are often worried about patient tumour types because if detection is not done properly then doctor cannot save the life of patient therefore it is called a dangerous disease and detection .But some different techniques can make easier this task. First take dataset then apply preprocessing then after this apply feature extraction techniques with cvip tool after that different classifiers applied include Naive Bayes with accuracy 90% , BOVM based SVM with accuracy 97.3% and CNN with accuracy 98.5%. So through this result concluded that CNN gives better results with accuracy include 98.5%.So in this methodology CNN is a good classifier for the detection and classification of brain tumour patient and doctor can easily start the treatment of patient with this technique and can also save a life of human beings.

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