

# An effective brain tumor identification and classification using advanced Machine Learning techniques

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## Abstract:

The brain is an integral part of the human body responsible for regulating and controlling all vital life activities related to the body. A tumor is a mass of tissue formed from the collection of abnormal cells. A brain tumor is a tumor that forms or migrates into the brain. To date, no primary cause for brain tumors has been identified. Although brain tumors are not very common, brain tumors make up only 1.8% of the reported tumors worldwide. The mortality rate of malignant brain tumors is very high because it is an essential part of the body for tumor formation. Therefore, it is essential to accurately diagnose brain tumors at an early stage to reduce mortality. Therefore, we suggest a computer-assisted radiology system to diagnose brain tumors by MRI scans to diagnose brain tumors. In this study, we implemented a model of image separation using the Basin and PSO algorithm. It captures features using DWT and PCA algorithms. It classifies tumors using high-accuracy rates CNN, Support Vector Machine (SVM) and Lacey IBK algorithm.

Keywords: Brain tumor, Classification, Prediction, Machine Learning.

## 1. Introduction

There are infinite cells in the human body. When cell growth is uncontrolled, the high mass of the cell becomes a tumor. CT scans and MRI scans are used to detect tumors. This study's contribution is to accurately diagnose brain tumors and classify them using a variety of technologies. It includes computer image processing, sample analysis, amplification, and brain analysis classification for medical image processing. Neuro-surgeons, radiologists can use the system, and health professionals to improve the specificity, sensitivity. The diagnostic efficiency of brain tumor screening using Matlab, an industry-quality simulation software. These technologies include MRI scans collected from online cancer imaging archives and scans from various pathology laboratories. We resized the images and applied a specific algorithm to sort and sort. The system hopes to improve the brain tumor screening process currently in use and reduce health care costs by reducing the need for follow-up procedures. Accurate characterization and analysis of biomedical image data require several processing steps. Our study is related to the detection and classification of automated brain tumors. Brain anatomy is usually diagnosed using an MRI scan or CT scan. The goal of our system is to detect the tumor for a given MRI scan, which, if detected, classifies the tumor as malignant or empty. The motive behind this paper is to support neurosurgeons and radiologists find brain tumors in a cost-effective and non-invasive way. The main goal is to produce a method for growing, differentiating, and classifying brain tumors. The system can be used by neurosurgeons and health professionals to integrate image processing, sample analysis, and computer vision techniques. It is expected to improve the sensitivity, specificity, and efficiency of brain tumor screening. The optimal combination and parameterization of the above steps allow the development of tools to determine or monitor clinical approaches.

## 2. Related Works:

In clinical diagnosis, algorithms' accuracy and precision are essential because they are essential for treating patients. Many available taxonomies and clustering algorithms are used for this. The goal of medical image clustering is to analyze the image as a meaningful image. Many clustering and classification algorithms aim to increase the predictive accuracy of the diagnostic process in detecting abnormalities. Pre-processing and amplification methods improve a suspicious field's detection using a magnetic resonance image (MRI). This section introduces a gradient-based image enhancement method for brain MR images based on previously received and localized data.

The preprocessing and improvement method consists of two stages; First, image artifacts like labels. X-ray markers were removed from the MRI using a tracking algorithm. Second, the removal of high-frequency frequency components using a sizeable average filtering method [12]. It offers a higher resolution MRI than average filters, custom filters, and local filters. The proposed method's performance is measured using the specified single-noise ratio (PSNR) and the average signal-to-noise ratio (ASNR). Image separation is the primary step and the most critical task of image analysis. Its purpose is to capture from the image using the image partition. Medical Image Segmentation has established a complete application for patients in various fields such as automation judgment, treatment management planning, and computer integrated surgery. Edge detection is a commonly used method for tapping images based on abrupt changes in intensity. The Coni Edge operator operates in a multi-step process. The CANI algorithm is the only process that creates an unbroken edge to the posterior border of the brain [5]. Oz's range is a linear function that converts a grayscale image into a binary image. Two steps are assigned to pixels less than a specific limit. The two phases of the binary image are assigned to pixels below or above a specific entry. It depends on the range of statistical calculations. Ozu suggested reducing the weight of the object's class differences and the background pixels to establish a better range.

### 2.1. Particle Swarm optimization:

An algorithm based on animal intelligence has been developed that follows the collective behavior of searching for food resources [6]. Each solution in the PSO algorithm is a bird in the search area, called a "piece." All cells' fitness value is estimated by the speed data that provide the fitness function and compatibility. In the problem area, the cells move according to the most convenient solutions available. The algorithm starts with randomly generated solutions (cells) and searches for the appropriate solution [7]. At each iteration, all adequate cells are updated according to the two best values. The first of these best values is a cell that has been discovered so far, called the "best." The other is the best value found for any cell in the population. This value is the world's best value for the population and is called "G-BEST."

### 2.2 Watersheds:

Basin separation is a gradient-based separation technology. It treats the image gradient map as a solution map [9]. It divides the picture into a dam. Divided areas are called fishing grounds. Basin partitioning solves various image partitioning problems. It is suitable for films with high moisture value. Marker-controlled basin partitioning is used to control excessive partitioning. The social operator is ideal for finding the edge [10]. In the marker-controlled watershed section, the Sobel operator is used to collect the material [11].

### 2.3 Feature Extract

Feature extraction is the extraction of quantitative information from an image such as color properties, texture, shape, and contrast. Here we use Discrete Waveform Transform (DWT), and Gray-Level Co-Insurance Matrix (GLCM) for Statistical Feature Extract for Wavelet Coefficient Extract.

### 2.3.1 Discrete Wavelet Converter:

The wave was used to analyze the variables of different frequencies of the image using different scales. Here, we use a Discrete Waveform Transform (DWT), a powerful feature extraction tool. It was used to distinguish violet modules from brain MR images. The wave localizes the frequency information of the signal activity required for classification. The images are uses 2D discrete violet conversion subdivided into spatial frequency frequencies. It separated from the LL (low-low) sub-band, and the HL (high-low) sub-band has a higher performance than the HL (low-low). ), We used LL (low-low) and HL (high-low) for better analysis, which describes the image-text properties [21].

### 2.3.2 Principal Component Analysis:

The most successful technique used in image recognition. The main component of compression is analysis (PCA), which is used to reduce large volumes of data. The primary method is to calculate the co-data-variant matrix's eigenvectors and calculate them by a linear combination of the principal eigen vectors. With the PCA process, the test image can be detected in advance, and the image can be pasted into the ego-space. To achieve complementary weight training and to compare face weights in the training group [21].

## 2.4 Classification

In classification tasks, several candidate attribute extraction methods are available. The most suitable method can be selected by training the nervous system to perform the required classification tasks using different input features. Error in neural response to test events Indicates an ance picture of associated input characteristics (method of obtaining them) for associated classification functions. The taxonomy algorithms implemented are as follows:

### 2.4.1 Lazy IBK:

Question Training Laziness practitioners collect training programs until the question is sent to the training process. There are benefits to learning from laziness. Main function k - The target function calculates the nearest neighboring algorithm locally. It allows the lazy system to work in parallel, solving many problem areas, and managing changes simultaneously [17]. On the other hand, lazy learning negatives indicate the need for large storage space to store the entire training dataset. IBK is a classification of K-close neighbors. Another search algorithm can be used to speed up the task of finding nearby neighbors. Distance search method parameter used with IBK. The classification window manages a limited number of training events that control the size selection [18].

### 2.4.2 Support vector machine:

SVM is a classification technology used in various fields, including facial recognition, text classification, cancer diagnosis, glaucoma diagnosis, and gene expression data analysis [15]. SVM affects the general or tumor classification of the MR image of the brain. SVM divides the given data into decision surfaces (i.e., hyperplane), which divides the data into two categories. The main goal of SVM is to increase the margin between two class hyper-aircraft. Input reduction for SVM and specific feature sets is provided during training and testing. SVM is based on binary classification, which utilizes supervised practice to provide the best results [22] [23].

## 3. Procedure: Detection and classification of brain tumors using advanced ML.

In this paper, we have implemented nine algorithms. A detailed description and various products are shown below:

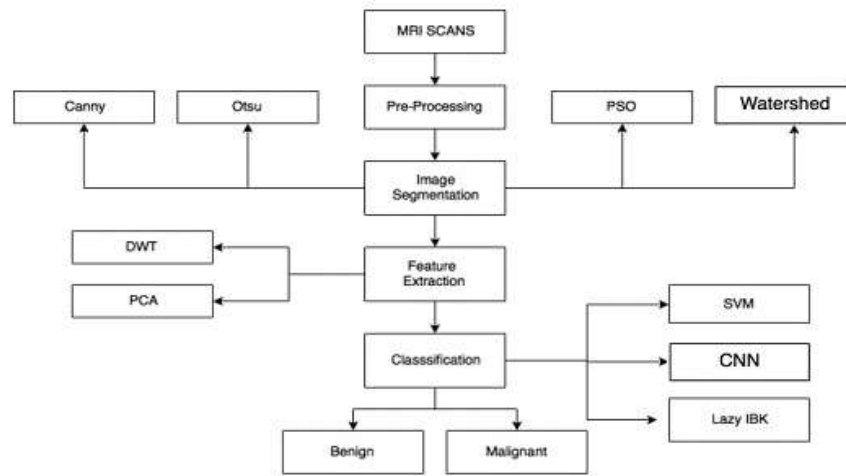


Figure 1: Preprocessing flow diagram for the detection and classification of brain tumors using advanced tumors

Figure 1 shows the different stages of our system development. The diagram shows the interactions between the application's various components and their positions in the development hierarchy. Therefore, this style is suitable for the selected problem because all the selected problem modules work independently. Communication through the messaging connector is perfect. The flow of the system is from top to bottom.

### 3.1 Used for dataset analysis

Data was collected from various verified sources and then divided into two types:

- Cancerous (Malignant)
- Non-cancerous (Benign)

Canny Edge Detection is a technology that significantly reduces the amount of data that can be used to collect and process useful architectural information from various visual objects. It is widely applied in various computer vision systems. Kanye found that application requirements for edge detection are very similar in different vision systems. Therefore, an edge detection solution can be applied in a variety of situations to meet these requirements.

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Algorithm-1: The Cone Edge Detection Algorithm process can be divided into five different stages:

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Step (i). Apply Gaussian filter to smooth the image to remove noise

Step (ii). Find the intensity gradients of the image.

Step (iii). Apply non-maximum suppression to eliminate over-reaction to mark the edge

Step (iv). Apply double edge to determine possible edges

Step (V). Track edge from cervix: Complete edge marking by pressing all other weak edges without attaching to the firmware's edges.

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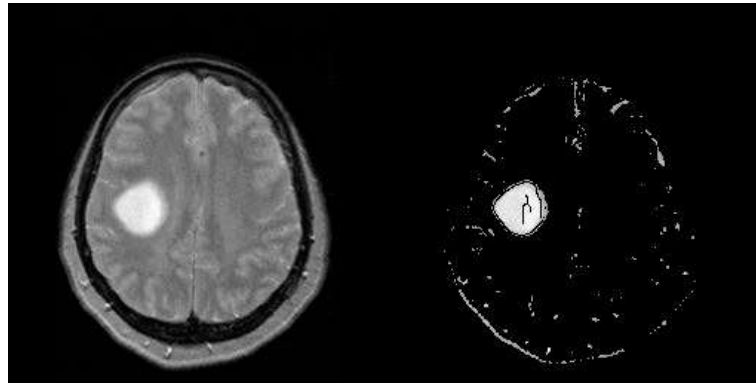


Figure 2: Place the output from the CANI algorithm.

### 3.2 Ots algorithm:

In image processing, the Nobuki Otsu name Oats method automatically reduces the grayscale image on a clustering-based image threshold or binary image. The image has two class pixels, and then the algorithm Ums a dual-model histogram (front pixels and background pixels). It calculates the correct range that separates the two classes. Their mixed amplitude (intra-class difference) is at least equal (because the sum of the square distances in pairs is constant). Their inter-class variability is maximal.

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Algorithm 2: The algorithm continues:

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1. Assess the histogram and probability of each severity level
  2. Set the probability and average of the starting class.
  3. All possible limits are  $t = 1, 2$ . Go through the maximum intensity
    1. Update and average class opportunities
    2. Calculate the intra-class difference
  4. The required range corresponds to the maximum intra-class difference.
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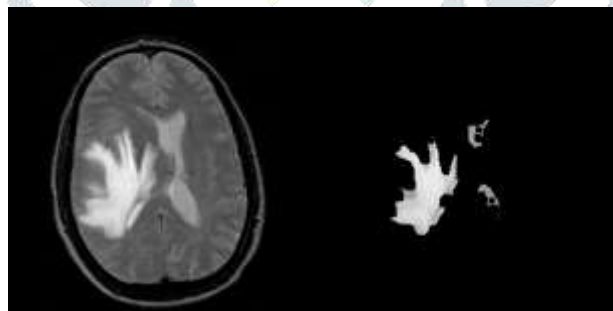


Figure 3: Otsu Algorithm

### 3.3 Watershed algorithm.

Any grayscale image can be seen as a topographical surface. It reflects high-intensity peaks and hills, depicting low-intensity valleys. We start filling each valley (local minimum) with different colored water (labeled). As the water rises, it begins to merge with different peaks (slopes) of different colors, from different valleys. To prevent it, we create barriers at the points where the water emerges. We fill it with water and create obstacles until all the peaks sink and the restrictions created to lead to disintegration.

However, this method can cause much psychological discomfort due to any manipulation of the sound or image. Therefore, we implemented a basin algorithm based on a composite marker for all valley points. It is interactive image segmentation. Label the area we know for sure as a color front or object. We label an area where we are sure there will be no different color background or object, indeed, label with field 0. None of us know for sure. Then we apply the basin algorithm. We will update our marker with the label we entered, and the range of items will have a -1 value.

The watershed section that controls the marker follows this critical process:

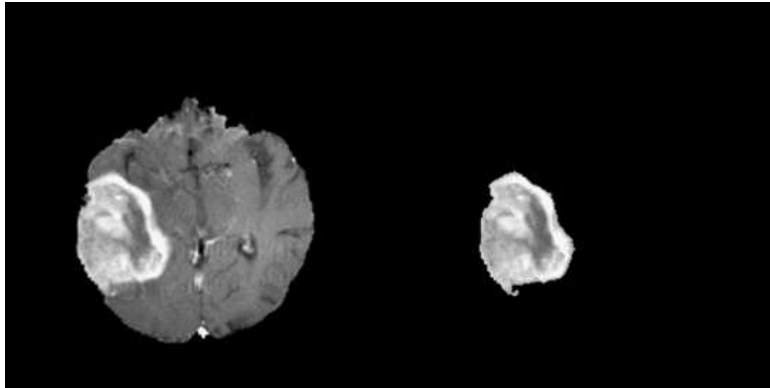


Figure 4: Output from the basin algorithm (malignant)

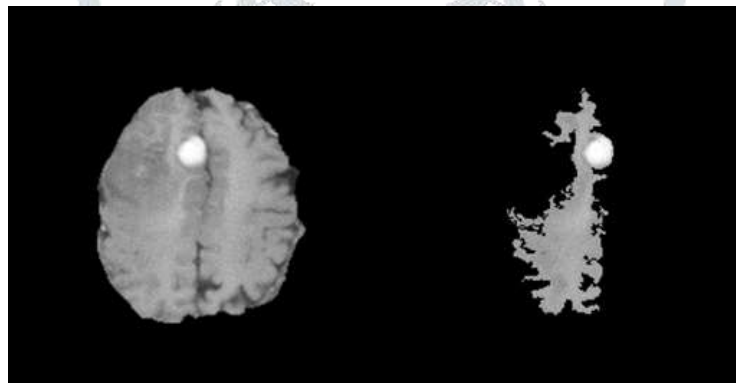


Figure 5: Output from the CANI algorithm (Benin)

#### 4.4 Particle Group Optimization (PSO)

The PSO algorithm starts by creating random positions for the cells in the starting field. The pace usually starts earlier. However, during the first iteration, the cells can be set to zero or small random values to avoid leaving the search space. During the algorithm's main loop, the cells' speed and position are repeated until the stopping criterion is reached. Updated rules:

$$v_i^{\rightarrow t+1} = wv_i^{\rightarrow t} + \varphi_1 U_1^{\rightarrow t} (b_i^{\rightarrow t} - x_i^{\rightarrow t}) + \varphi_2 U_2^{\rightarrow t} (l_i^{\rightarrow t} - x_i^{\rightarrow t}),$$

$x_i^{\rightarrow t+1} = x_i^{\rightarrow t} + v_i^{\rightarrow t+1}$ , Where  $w$  is the parameter called the static weight, and  $\varphi_1$  and  $\varphi_2$  are the two parameters called the acceleration coefficients, and  $U_1^{\rightarrow t}$  and  $U_2^{\rightarrow t}$  are both  $n \times n$  diagonal matrices. The entries in the main diagonal are evenly distributed at random intervals  $[0,1]$ . During each iteration, these measurements are reproduced. In general, the vector  $l \rightarrow t$  calls them the best neighborhoods - the best place to find any particles in the cell environment. Assume that the values of  $w$ ,  $\varphi_1$ , and  $\varphi_2$  are appropriately selected. In such a case, the velocity of the particles is guaranteed not to increase to infinity.

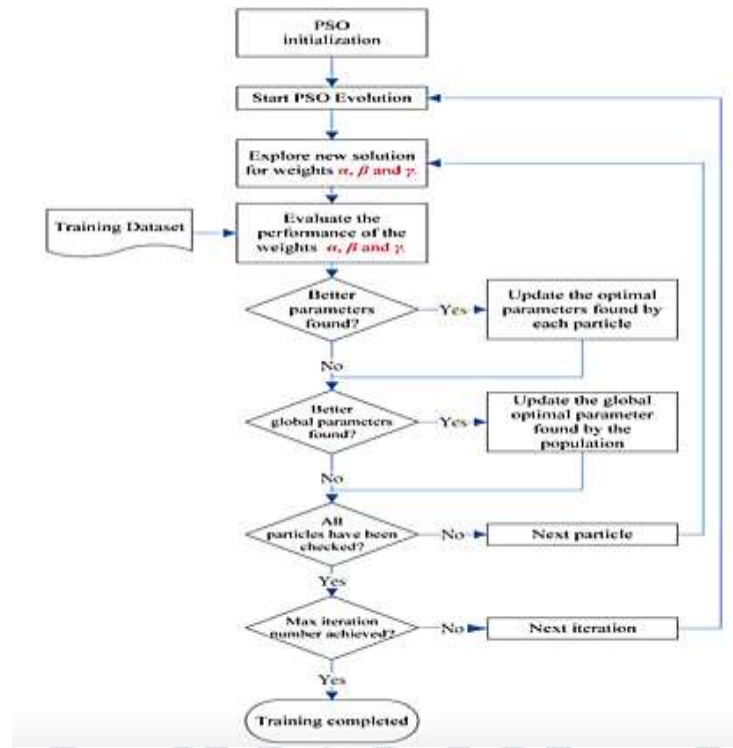


Figure 6: PSO algorithmic flow chart.

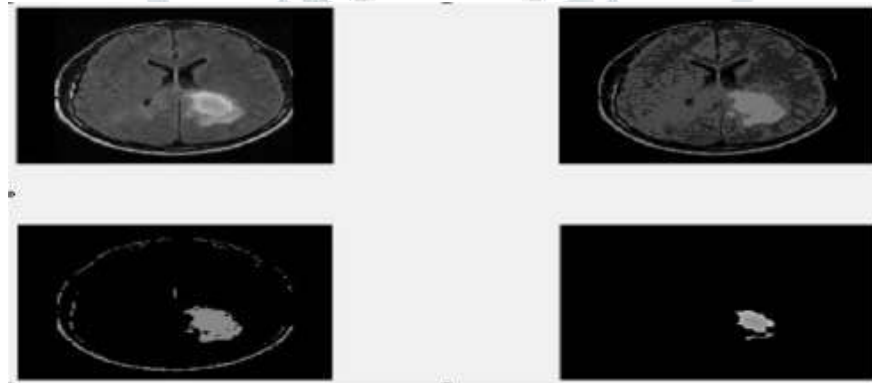


Figure 7: Output from the PSO algorithm (malignant).

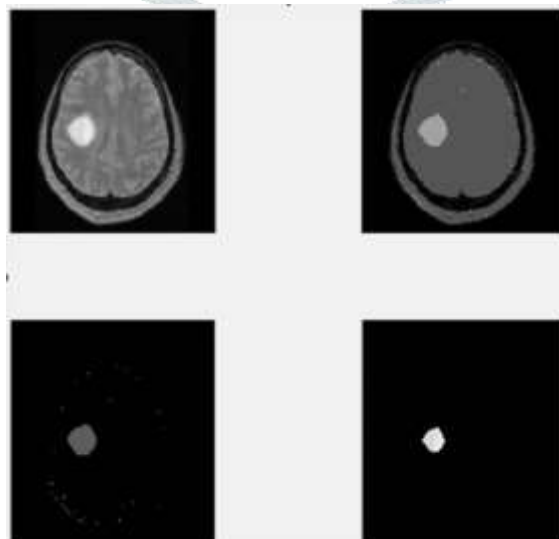


Figure 8: Output from the PSO algorithm (Benin).

#### 4. Summarize the feature

##### Discrete Wavelet Transformer (DWT) and Principal Component Analysis (PCA) with Gray-Level Co-Availability Matrix Algorithms (GLCM).

Discrete Wavelet Transformation (DWT) is a robust implementation of WT using diode scales and positions. Demonstrate the basics of DWT as follows. Here, wave,  $a$ ,  $b(t)$ , and wave translation are calculated from the mother wavelength ( $t$ ).  $A$  is the translation factor, which is the translation parameter (both are real numbers). In the development of violet analysis, there are many types of waves that are popular. The most crucial wave is the hair wave, which is the most straightforward and most frequently preferred wave in most applications. GLCM is a used system for healing image analysis and classification. This method provides information about the relative positions of two pixels relative to each other. GLCM is calculated by counting the number of pixel pairs at a given distance. To calculate the GLCM matrix for Figure F ( $i, j$ ), the distance-vector  $d = (X, \text{defined.})$  ( $I, j$ ). The element of the GLCM matrix  $P$  is defined by the grayscale  $I$  probability. It is defined as  $J$  occurs in extension and angle. GLCM Matrix  $p$ . Four distances (1,2,3,4) can be used to extract design features from four angles (0,45,90,135) and calculate the co-event matrix.

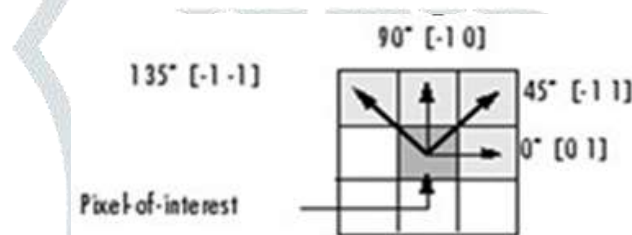


Figure 9: Calculation of the co-occurring matrix in GLCM

#### 5. Classification

##### 5.1 Support Vector Machine (SVM)

Support vector machines (SVMs) monitor learning patterns and associated learning algorithms, analyze data, and identify different models used for taxonomic analysis. The actual SVM input takes some data and each given input. The output produces two classes, deadly and non-deadly, which is linear binary linear classification. The set of training samples each identified as one of two categories. An SVM training algorithm builds a model that gives new examples in one category or another. The SVM model represents examples of mapping space into points. Examples of individual classes are divided by apparent differences described in as much detail as possible. New examples are added to this, and they are selected into a category based on which trench they belong. Further, in practice, the support vector machine builds a set of hyperplanes in a high or infinite-dimensional space used for classification, regression, or other operations. The hyperplane achieves better isolation by using a greater distance to the nearest training data point of any class called the operating margin. In general, broad margin classification reduces the error of normalization. An SVM feature takes vectors as input, creates a training model after scaling, selection, and annotation verification, and presents the training model as .tput. The following figure indicates the training approach of the SVM:

##### 5.2 Lazy ebook

Example-based learning algorithms compare new problem events with memory observed during algorithm training. It is different from standard algorithms because it does not make explicit generalizations. It is called example-based because the training is made directly from examples. As the grass of Athos grows, so does the complexity of Athos. Worse,  $n$  OTAs hue  $n$  training equipment list. The new example is the computational



complexity of the taxonomy,  $O(n)$ . The data-based modeling methods considered so far are building the first available (training) data (learning process) model. It will be implemented when classifying or numerically estimating. These techniques are sometimes called intensive practice (because they are interested in creating a model first). Example-based (IB) learning methods collect training events and defer generalization (model building) until a new example is classified. The model created by IB methods is not a global model that uses all training data, but a native model with only a few examples. IB methods are used for classification and regression. Required methods include comparative neighborhood method, locally loaded regression, and case-based logic. Other names for IB methods include ideal, case-based, experience-based, and modified K-close neighbors. A semi-monitored learning algorithm is based on an example of a K-near neighbor. Training data and pre-defined K values are required to find the nearest K based on each example's distance calculation. Suppose there are different classes of K data. In that case, the ts algorithm assumes that the new data class is equal to the majority class—MX-by-n Data Matrix a.

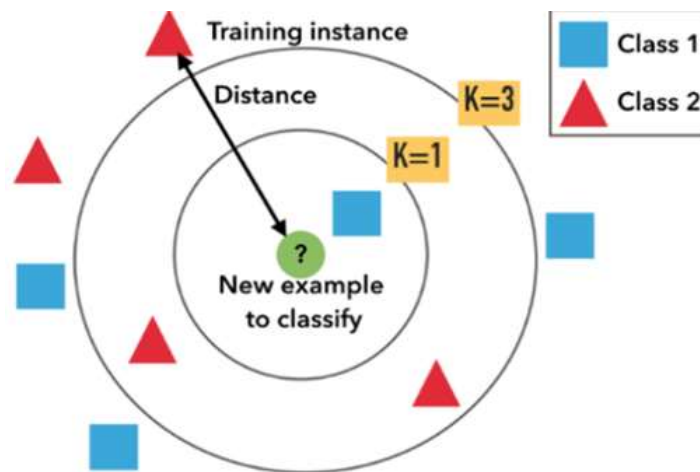


Figure 10: Example-based KNN

### 5.4 Sensory Neural Network (CNN)

Convergent neural networks (CNNs) are similar to traditional nervous systems, designed with learning loads and parasitic neurons. Each neuron receives multiple inputs, one of which calculates the load, undergoes the active function, and responds with one output [21]. The CNN algorithm is a unique design of a multi-layer concept to identify two-dimensional image information. It consists of the following layers: an input layer, convection layer, sample layer, and input layer. The neuron parameter is set to the same parameter of weight distribution, i.e., each neuron has a transition kernel similar to the Dionevolution image. The figure below shows the process implemented during CNN [21].

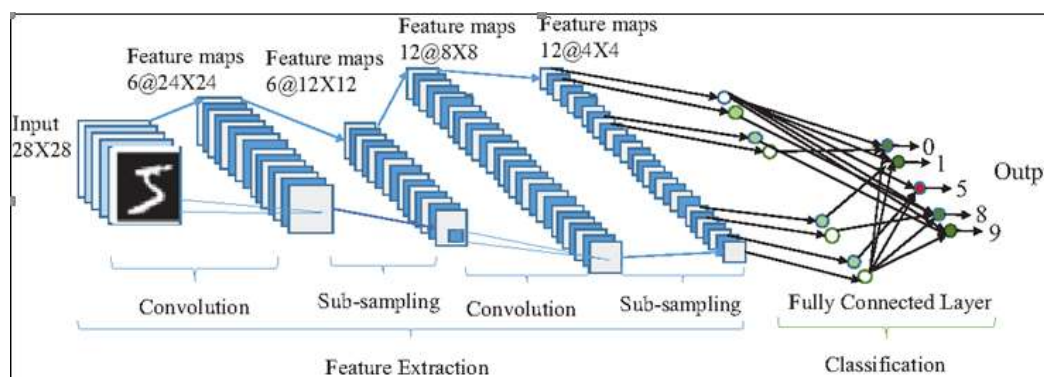


Figure 11: CNN block diagram.

The CNN algorithm has two main processes: conversion and modeling. It uses the Filter FX Convention process, which can be trained for input image conversion. The first step is the input image. The second input after conversion is a characteristic image of each layer. A feature map and then a bias box was added, resulting in a communication layer  $C_x$ . The sampling process adds pixels to each neighboring pixel, and the scaling weight is  $W_x + 1$  weight, followed by adding bias  $b_x + 1$ . The activation function creates a narrow n time feature map  $S_{x+1}$ .

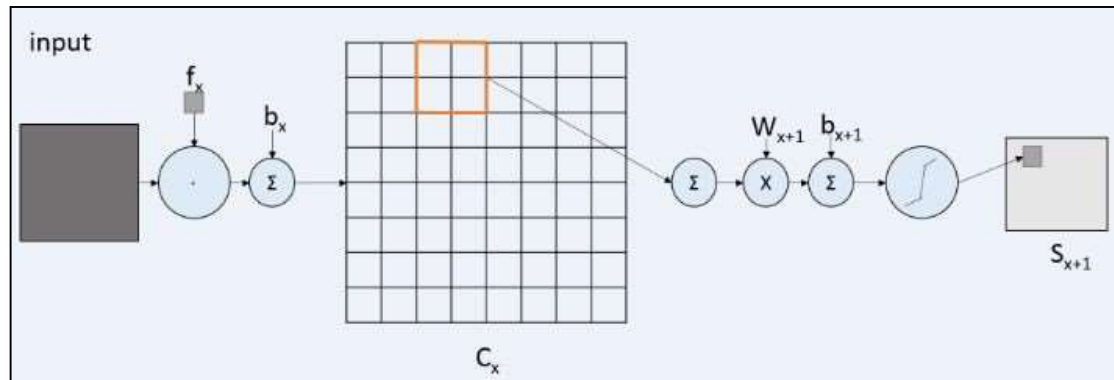


Figure 12: Work on CNN.

The CNN algorithm's main idea is to reduce the size of the sub-sample and training parameters according to the local acceptable field usage, weight allocation, and time or place of a feature collection. CNN is useful because it explicitly avoids facilities' work and seeks to learn internally from training data. Neuron weight properties are similar to those on the mapping surface, which reduces network parallel learning and complexity. Also, by adopting a sub-sample structure over time or space, viscosity, size, and deformation displacement can be achieved to some extent.

Figure 13: CNN process.

### 6. Results and discussion

Matlab (Matrix Laboratory) is a multi-model numeric computing environment and fourth-generation programming language. MathWorks' proprietary programming language allows matrix manipulation, plotting functions, and data to be implemented in MatLab algorithms. It creates user interfaces and interfaces with programs written in other languages. The output of the computing that executes all the classification algorithms is mapped using a false matrix. The matrix contains information about the actual and estimated classes that implement the confusion classification system. The performance of such systems can be estimated using the data in the matrix. The table below shows the confusion matrix for the two-level classification. The confusion matrix helps to determine the accuracy of the dataset. The mythical matrix shown has the following meanings in terms of data.

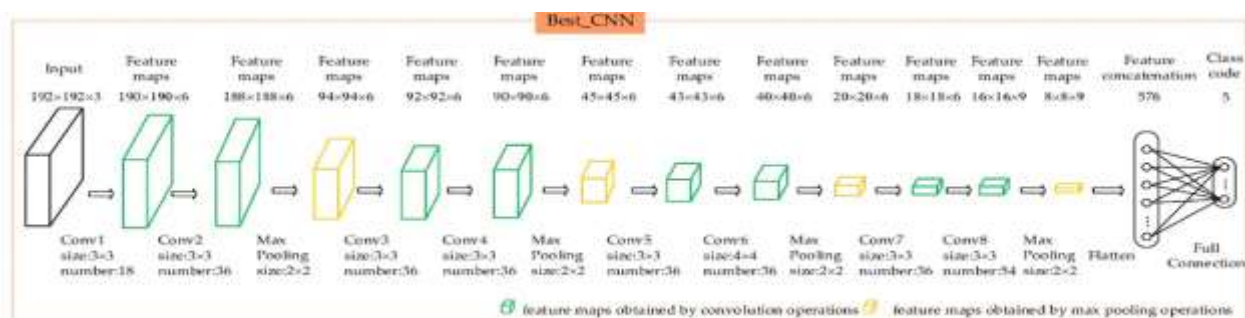


Table 14: Confusion matrix calculations.

An example of several gloomy accurate predictions,

Example B is the number of false assumptions that an example is positive,

Negative C is an example of several malicious and false assumptions.

Positive d, for example, is the number of positive optical predictors.

As described in Table 11, the test results above are presented here as confusing each probability.

## 7. Conclusion

Abnormal growth of brain cells affects the brain's normal functioning, which is considered a brain tumor. Medical image processing's primary goal is to find accurate and meaningful information using an algorithm, with as few errors as possible. Brain tumor detection and MRI image classification can be divided into four different categories: preprocessing, image segmentation, feature extraction, and image classification. Different segmentation methods are examined in the paper. It can be concluded that the algorithms and parameters used in the proposed system increase the system's efficiency by achieving better results. Border methods and edge-based approaches to partitioning are also popular. However, the growing scenario in this area gives good results. A particle group optimization algorithm has been found to give a very precisely named degenerative tumor. Extracted features using the GLCM method improve efficiency because minute details of the tumor can be collected using various features. Various classification methods studied experimentally have found that integrated neural networks provide better classification accuracy. Accuracy and reliability are essential in tumor diagnosis. The life of the patient depends on the results of the system. Therefore, the proposed method can help increase accuracy and achieve the desired result.

### 7.1 Future range.

Future activities promoted by these results will include improvements to the classification results and overall accuracy. It can also increase the number of output classes as more data becomes available. With more extensive and diverse datasets, the overall taxonomic accuracy will increase significantly.

To enhance the result is to raise the number of hidden layers of the nervous system. The weight can be adjusted well by increasing and sorting the number of hidden layers. The learning-tuning and transfer learning approach can also optimize the model based on previously trained models.

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