International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 06 Issue: 05 | May - 2022 Impact Factor: 7.185 ISSN: 2582-3930

Brain Tumor Detection Using Hybrid Model

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Abstract- *Computer-assisted diagnosis (CAD) has become more significant in medical applications to assist doctors in making appropriate judgments. One such application is the identification of brain tumours using MRI images of the brain. Several machine learning techniques have been developed to categorise brain MRI with varying degrees of accuracy. A dense net neural network model is utilised in this study to categorise a brain MRI picture into two classes: tumour and no tumour [1]. Identifying MRI brain tumours is among the most essential tasks in medical image analysis. A brain tumour is an uncontrollably growing and multiplying cluster of cells. It is created by unfavourable cells that are typically present in various parts of the brain, including as lymphatic tissue, glial cells, neurons, blood vessels, and the skull, or it is disseminated from tumours that are mostly present in other systems. To increase the models accuracy, the original dense net model is expanded with certain connection alterations in this study. When compared to previous deep learning models, the updated dense net model can acquire detailed information from an MRI picture and categorise it with more accuracy.*

Keywords*:* *Tumor, Support Vector Machine (SVM), Convolutional Neural Network (CNN), Hybrid-Model.*

1. Introduction

Tumor diagnosis from brain MRI images comes at a significant price in terms of both effort and time. Medical professionals may make mistakes in tumour choices because to exhaustion. It is possible that the subjects will die if the tumour is not detected. The individuals' survival rate can be improved if the tumour is detected early and treated promptly. Medical practitioners may make more accurate decisions in less time with the use of computer-aided diagnostic technologies [1, 2]. To classify illnesses, these systems employ a variety of image processing and machine learning methods.

The brain is the most significant element of the human body that does a lot of job Plex structures. The performance of the skull layer that surrounds the brain makes huge studies harder and increases the difficulty of disease detection. Brain sickness does not impact any other part of the body, while it may be triggered by aberrant cell proliferation, which eventually destroys brain structure and causes brain damage. Cancer. The Health Organisation, on the other hand (WHO). According to the research, there are around 9.6 million globally. People suffering from cancer died in 2018, as did 30 to 50 percent of those with primary tumor. Brain cancer is one of the worst types of cancer. As a result, statistics Nearly 17,760 persons have died as a result of brain tumours. In the year 2019, Because of the acute state and atypical development of cancer, as well as the intricacy of brain anatomy, a quick diagnosis is required. With high quality brain pictures, magnetic resonance imaging (MRI) is commonly employed for sarcoma analysis. MRI Technology is very vital in brain imaging because it provides a unique approach of Optimal viewing for both Spatial and Contrast Dieter Mining. It is frequently utilised in the MR imaging process to depict distinct phases of the disease that are suspected. Instability in the bottom right quadrant is significant.

Some of the most critical steps in computer-assisted diagnosis are listed below.

• Image Pre-processing

• Segmentation

• Recognition

• Acquisition

The first phase is image acquisition, which involves employing equipment like as cameras, scanners, and sensors to get images from various sources. The devices produce raw data, which must be converted to a digital format for storage using techniques such as sampling and quantization. The picture obtained in the previous step must be pre-processed so that it may be used in subsequent steps [1, 3]. The effectiveness of picture pre-processing determines how well subsequent processes work. The sort of pre-processing that should be used is determined by the needs of the application. The sort of pre-processing to be done to the picture differs depending on whether the image is in colour or grayscale. After pre-processing, segmentation comes next. The homogeneous regions of the picture are detected and separated at this step. This segmentation is used to locate parts of a picture that are similar. Segmentation separates the image's regions of interest. Segmentation is a crucial procedure in a variety of applications, including computer vision and illness diagnostics. The segmented picture is then converted into a format that may be used for further processing. The picture is then described in terms of characteristics for further processing in the image description, such as classification [2]. The following are a few of the most used descriptions.

Descriptors for boundaries and regions Border descriptors include features such as boundary length, diameters, eccentricity, and form. Compactness, texture, and topology are examples of regional descriptors. Picture recognition is the process of giving a label to a descriptor discovered during the image description stage. The X Research Scholar Department of Computer Science & Engineering, Sri Siddhartha Institute of Technology Tumakuru, Karnataka, INDIA Y Professor & Head Department of Computer Science & Engg., Sri Siddhartha Institute of Technology Tumakuru, Karnataka, INDIA image processing is the interpretation of images. In this stage, the picture is used to get the conclusion. The inference varies depending on the application requirements. Deep learning is the most recent trend in machine learning, in which characteristics may be learned automatically using convolutional layers without the need for a manual description [2, 1]. Deep learning models can learn detailed characteristics from photos in this way. In this study, a dense net deep learning model is used to classify brain tumours from MRI images. There are more links in the original densenet. Overlearning and accuracy might be harmed by the linkages. We suggest connection enhancements in the original densenet for enhanced accuracy in this paper.

2. Literature Survey

Brain tumour identification is considered an image segmentation challenge, with the purpose of recognising whether or not there is a tumour in the picture. In order to overcome this difficulty, researchers utilise MRI scans to evaluate a variety of deep learning algorithms and image processing technologies. The major problem in picture segmentation is grouping feature vectors that are similar. In modern image processing research, reasoning-based algorithms and thresholding techniques are common. Rough Extreme Learning Machine (RELM): -94.233 percent, Deep CNN (DCNN): -95 percent, Deep Neural Network (DNN) with Discrete Violet Auto Encoder (DWA): -96 percent, K-Neighbourhood (KNN): -96.6 percent, CNNN: -97.5 percent, hybrid CNN-SVM: 98 percent Previous research samples. To achieve the system's great accuracy, the system is trained using a number of in - depth learning networks such as AlexNet, Google Net, Squeeze Net, ResNet 50 and ResNet 101. However, AlexNet is the most accurate of the three.

Sherlyn and Murugan [3] used a hybrid model of the K-neighbourhood (KNN) and used a blurred C-means approach to classify and cluster tumor cells at an early stage from MRI scans using 2D medical images of the brain. Tried.

Among those who have contributed to this work are Sherin Saeed et al. [4–2]. Based on the moth-flame optimization (MFO) approach, the same research proposed a segmentation method for organising abdominal instances of liver MRI images. Similarly, it employs the Structural Similarity Index (SSI) to choose the best-fitting output and obtains a test accuracy of 95.66 percent. Although NN and threshold-based tumour differentiation are common, most research suggests that they may be used with KNN to improve outcomes [13]. Machine learning techniques, which can be time consuming, can be used to identify brain tumours. The importance of human perception and feedback in machine learning cannot be overstated. In the meanwhile, various ML-based studies are being carried out to accelerate this process.

One of the researcher used the Firefly algorithm to develop a novel approach to tumor detection. In the fireflies' method, a chemical process called bioluminescence occurs in their body and produces light, which makes it possible to accurately identify and retrieve tumors from MRI data of the brain.

Among those who have contributed to this work are Mainz et al. [4, 4]. Benchmark findings for multimodal brain tumour segmentation were presented, based on 65 low- and high-grade multiple-contract MRI patients. Meanwhile, it employs simulation software and the Conventional Human method to display the partition's complexity on a scale from 0 to 100. (74 percent - 85 percent). And the outcome demonstrates that algorithms based on regions and achieving that level may function at a higher level. In some ways, DL is a NN-based architecture [5], but it is an ML technique that allows for the addition of numerous hidden layers between the input and output layers. Speech Recognition [6], Object Recognition [6, 1] and Picture Classification [6, 2] are some of the domains that can be used. DL architecture is commonly used with CNN [6, 4], which allows for easier management of input, hidden, and output layers [7]. The standard CNN approach, on the other hand, determines whether an object is present in the image, but its position is not.

This approach has produced an optimal effect and precision in the distinction, characterization, and identification of brain tissue and tumours. AlexNet, VGG 19, GoogleNet, ResNet 18, VGG 16, ResNet 50, and ResNet were among the PTNs employed in their research. Transfer Learning using Inception-V2, ResNet101, and CNet for BT categorization (TL). First, they tailored the last three layers of PTN to their taxonomic research. Following that, the completely connected layer is replaced with fresh layers in their original PTN, BT kinds are distinguished by their external unit. Ultimately, they experimented with MR data using the TL-based Fine-Tune PTN. Their explanation indicates that, even with tiny datasets, TL produces consistent findings.

Recognition of lung cancer, and brain cancer can benefit from DL, which is a versatile and highly effective approach [7, 1]. Automatic segmentation of multiple MRI datasets can be done effectively using in-depth learning algorithms. The CNN method for automated brain MRI image segmentation has shown successful results by considering a number of factors [7, 2]. According to recent studies and solutions to this problem,

Hossam, et al. [8] Brain tumor MRI proposes multiple classification based on DNN, which attempts to create a new model with two publicly available datasets that first define the tumor type, and then define the glioma grade of the detected image.

Son and others. [8, 4] Focus on recent advances in machine learning (ML) for large data systems and a number of strategies in the context of current scheduling for specific cultural applications.

Chatterjee aims to provide a substantial understanding of the many difficulties and obstacles of the IoT in BD strategy and the pragmatic approach based on the ML strategy.

Using machine learning approach, Jinji et al. [9] Display position system, Chatterjee briefly explained how machine learning (ML) can be applied in bioinformatics.

Jain and Chatterjee [9, 2] provide an overview of current and emerging machine learning (ML) standards in health informatics, reflecting the diversity, complexity, depth and breadth of this multidisciplinary field. It can be argued that the process of studying and testing brain tumors is fraught with difficulties. There is a problem with this study, which in many cases interferes with the author's views, but this problem has been overcome with the evaluation and allocation of general databases. In the next step, the author will examine the best models and use the existing research to design this research, it should be noted that it took a long time to design the research and optimizing the model and putting it together is one. Challenges in the research process, successfully overcome. After conducting several evaluations, the author found that the proposed approach could be applied to different domains by providing comprehensive information and improvements on the subject.

Deep learning (DL) is a sort of AI technology that mimics the activities of the human brain in data processing and the creation of helpful models for making suitable decisions. DL computation various non-linear layers that are well organized are used to capture visual characteristics. Each layer ordered contributes to the subsequent, and it aids in the purposeful discovery of knowledge as we go deeper into the system. Convulsive neural networks (CNNs) are part of the deep learning (DL) family and are often employed in exploring sequences with minimum pre-processing. The main results of this study are as follows:

The suggested hybrid model combines CNN and SVM for classification with threshold-based partitioning, resulting in a total accuracy of 98.4959 percent.

The suggested hybrid model that considers the advantages of both CNN and SVM models has been significantly improved.

3. Convolutional Neural Network

An in-depth learning method is used to organize the data into four objective elements and to verify its accuracy for each point. Only a few probes were transmitted from this useful resource using different taxonomies. Deep learning, often referred to as neural artificial networks, is a type of AI that manages computations driven by the brain's anatomy and ability. The large realization used to describe the advancement of new technology in ANNs to manage large amounts of information and increase the accuracy of data classification separates it from the nervous system [10]. The Convulsive Neural Network (CNN) is a unique neural network that has proven to be effective in generating information in image, text and sound structures. To demonstrate its network, the expression "convolutional neural network" created a quantitative function called convolution. The evolution operation is a dot product between the input matrices of the process. The operation of the CNN is shown in fig.

The local area of the previous layer is connected to the next layer in the convolutional neural network. In terms of spatial relationships, the CNN forms a neighborhood using a progressive example of communication between neurons in adjacent layers. Previous layer subunits are linked to single-layer units. The width of the map is determined by the unit number of layers in front of it [11]. The Lanette-5 serves as the inspiration for future iterations. In any case, CNN loads just like traditional multilevel systems; the size of the accessible ranges does not differ significantly from the input measure.

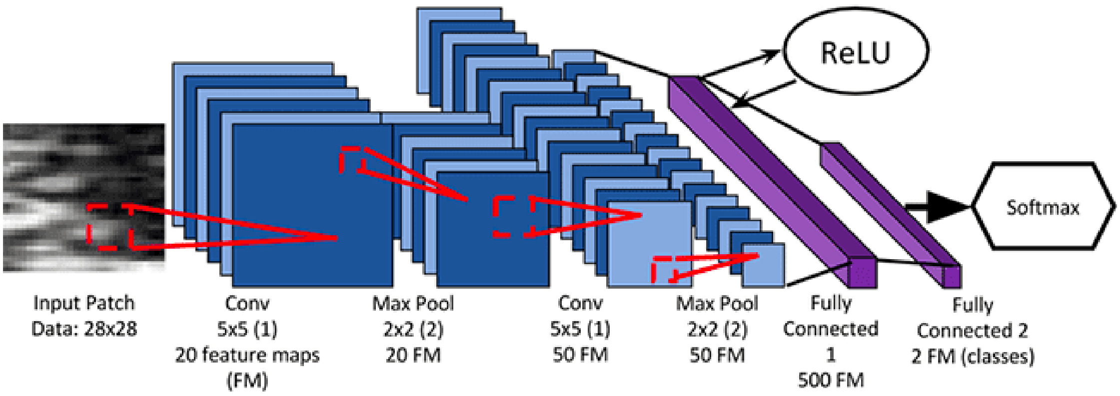


Figure 1: Convolutional Neural Network Architecture

These optimization strategies are used in the training phase to improve DCNN segmentation accuracy by optimising the output of the result vector [12]. The images of MRI brain tumours from the dataset were studied in this study. There are 220 high-grade gliomas in this sample, and 54 low-grade gliomas in this dataset. 53 people with a mixture of high- and low-grade gliomas were used in the study.

4. Proposed Architecture

The suggested effort improves the performance of traditional classifiers. These classifications are suitable for computer-assisted brain tumor identification and classification because they require very small datasets for training and minimal computational time complexity. We provide a hybrid aggregate methodology that incorporates CNN as well as other optimization techniques. Its goal is to calculate the area of the tumor and to classify benign and malignant brain tumors. Neural network architecture and execution are used to model the human brain. Neural networks are commonly used for vector scaling, estimation, data clustering, pattern matching, optimization tasks, and classification methods. It is classified into three categories based on neural network interconnections. Neural networks are classified into three types: review, feed forwards, and recurrence. There are two forms of feed forward neural networks: single layer and multilayer. A single layer network does not have a hidden layer. It does, however, just have one input and one output layer. Multilayer, on either hand, is made up of three layers: input, concealed, and outcome. A recurrent network is a feedback network with a closed loop.

In classic neural networks, image scalability is difficult. A picture, on the other hand, may be scaled (length, width, height) using a convolutional neural network (that is, it can be transferred from a 3D input volume to a 3D output volume). The Convulsive Neural Network is comprised of input, convergence, the Rectified Linear Unit (ReLU) layer, the pooling layer, and the fully connected layer (CNN). The convolution layer divides the provided input picture into smaller pieces. Layer-by-layer activation is handled by ReLU. There is no requirement to utilize a pooling membrane. We may either use it or ignore it. The pooling layer, on the other hand, serves more as a sample. The Support Vector Machine was developed as a robust tool for ordering and retrieving in a noisy, complex environment. Unlike traditional methods of imposing limits, improper observation preparation promotes vector T, which attempts to keep the upper limit of the machine to the maximum limit of the probability range. The mistake that can easily get your claim denied is to fail. The image object detection process determines whether there is an ingenious conflict in the photograph. The data picture is retrieved using the Image Object Detection Framework, which searches for objects of interest. This hunt is accomplished by edge-cutting small districts called look windows, which are the size of mxn pixels and undergo some form of pre-processing (histogram equivalence, highlight extraction) to determine if they are processed by a classification algorithm. They are the conspiracy involved the opposition.

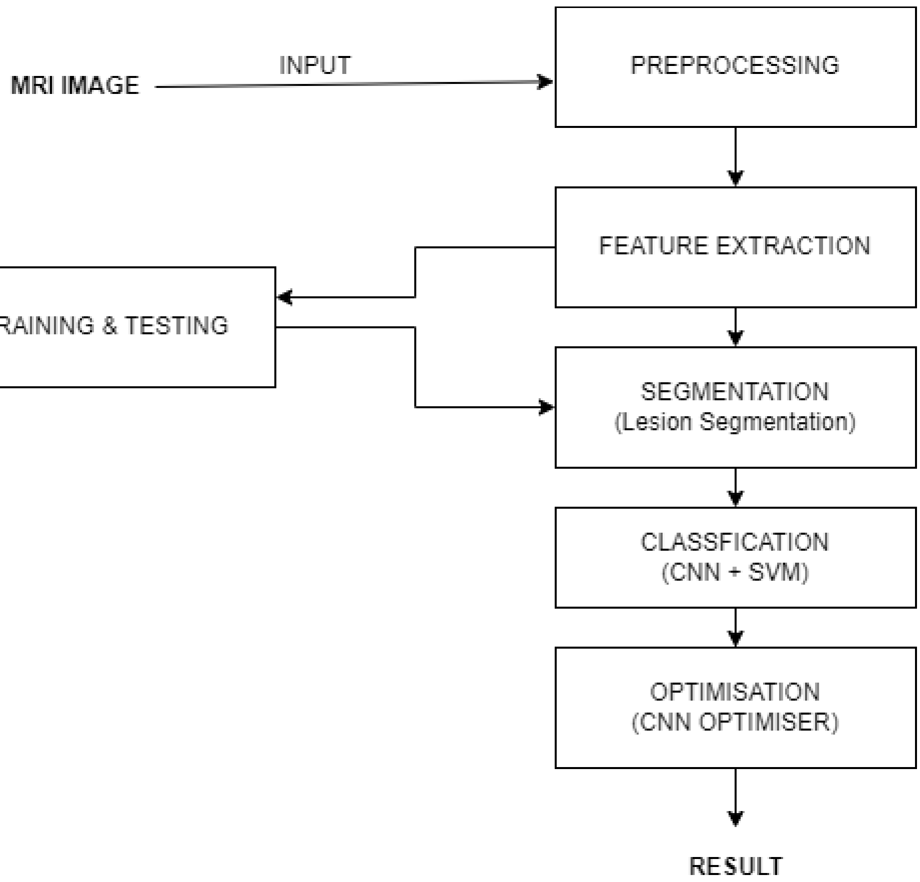


Figure 2: Proposed System Architecture

The Figure shows the proposed system in which there is various levels in which tumor can be classified and at the last result. The MRI scanned images are used in a large dataset and then classification took place.

5. Dataset

Our Dataset contains tumor and non-tumor MRI images and collected from different online resources. The Dataset link is given below:

[Data Set]

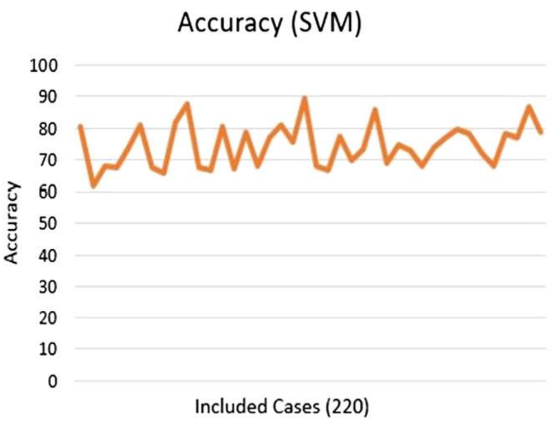
6. Results and Discussion

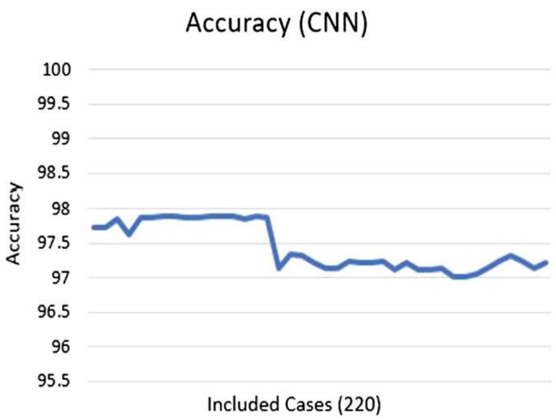
According to the suggested technique, after preprocessing, the extracted feature will be processed and placed in specified tests and train categories, taking into account training and testing. Using the activation function, the CNN model extracts the features and transfers them to a fully connected layer via multiple phases [15]. The CNN classifier will be trained using the retrieved picture characteristics. The SVM model, on the other hand, uses the CNN's fully linked output as an input to train each picture. The classifier will categorize the type of brain tumor at the final stage. Finally, the accuracy of the proposed hybrid CNN-SVM is assessed using the assessment specified parameter. When compared to current models, the new method produced better results. The accuracy of existing methodologies is compared to the proposed model in Table. Meanwhile, the total accuracy of hybrid CNN-SVM is 98.50 percent.

METHOD	ACCURACY
1. Regularized Extreme Learning Machine (RELM)	94.2%
2. Deep Convolutional Neural Network (DCNN)	95%
3. K-Means, K-nearest neighbor (KNN)	96.6 %
4. Convolutional Neural Networks (CNN)	97.5%
5. Hybrid (CNN + SVM)	98.5%

Table 1: Comparison of existing models with proposed Hybrid CNN and SVM.

If we look at the graph in Fig.8, we can observe that the accuracy level of CNN and SVM independently does not exhibit excellent development, which is supported by the information in Table 1. At the same time, the suggested hybrid CNN and SVM accuracy degrees both show substantial development.





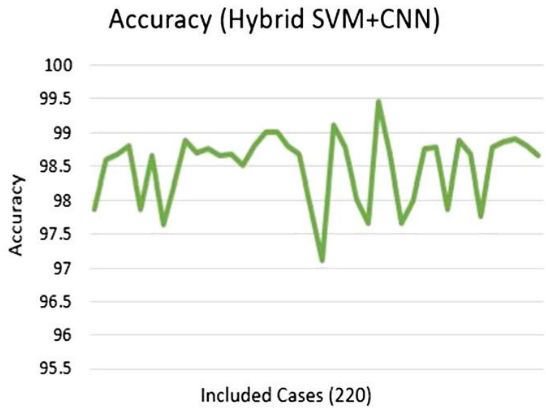


Figure 3: Accuracy comparison of CNN, SVM with Hybrid CNN-SVM model

7. Conclusion

The approach suggested in this study used the MRI scan image as the source for the multi-layered convolutional layer. Instead of using shallow designs with heavy filtering methods, we studied the capabilities of CNN architectures by creating small kernels [16]. We have noticed that even when using a large number of feature maps, narrow designs work poorly. This process, in addition to classifying brain cancers as yes or no, categorizes them into four types: glioma, meningioma, pituitary, and no tumour. The suggested system has a 98.49 percent average accuracy. Datasets including MRI scans of all three forms of brain tumours may be utilised to put a fully automated system to the test. Based on the enhanced quality of the suggested hybrid approach, this aids in the development of computer-aided systems for early identification of treating cancer and allows clinicians to increasing the accuracy sufferers. CNN is a machine learning technique that pulls data from brain MRI images [17]. For improved performance, combine with multiclass SVM CNN features. The proposed approach outperforms existing technologies in terms of total taxonomic accuracy by 98.49 percent. Extensive experiments on various MRI datasets for the brain are done to validate the increased performance of the proposed model. For CNN features, the SVM classification outperforms the non-linear activation model when the amount of training data is limited. Compared to transfer learning-based classification, CNN-SVM technology uses less computation and memory [18].

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