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Article Title: **Brain Cancer Detection Using Advanced Deep Learning Algorithm**

Brain Cancer Detection Using Advanced Deep Learning Algorithm

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ABSTRACT

The disease needs to be treated cautiously because of the complexity of brain cancer. Since each patient's brain tumor is unique in terms of dimension, shape, and localization, it is challenging to identify them in medical imaging. Magnetic Resonance Imaging (MRI) process is used to diagnose the brain tumor anatomy results in inaccurate detection of the tumor and it is very time-consuming. Therefore, many classification techniques from Machine Learning (ML) and Deep Learning (DL) are utilized to rapidly recognize the tumor. This paper proposes segmenting and detecting the brain cancer using Deep Convolutional Neural Network (DCNN). An image is first pre-processed using a median filter to minimize noise in the image. Global thresholding is a simple image segmentation technique that uses a single threshold value to separate an image into distinct regions. After that, the feature extraction method of Histogram of Oriented Gradients (HOG) is employed to detect brain tumors with higher accuracy and lower computational complexity than other methods. This performance measure is applicable to quantifying the performance of the segmented tumor region. Additionally, DCNN classification algorithm has achieved high performance and accuracy. For the purpose of identifying the performance of the model, this proposed project produced a confusion matrix. With a classification accuracy of 91.23% and a precision of 90.39%, the experiment's results demonstrated that the method is more successful than the current methods.
Keywords: Brain Cancer, Median Filter, Global Thresholding, Feature Extraction, HOG, Deep Convolutional Neural Network (DCNN).

1 Introduction

Abnormal cell development inside the brain is typical of brain tumors, which are pathological disorders that interfere with normal brain function and present considerable hurdles in terms of diagnosis and treatment. Because of their localization and rapid growth, brain tumors are associated with problems and mortality [1]. MRI early brain tumor, classification is crucial for the diagnosis of these conditions. For the identification of brain tumors, various diagnostic imaging techniques are employed. MRI's unique image quality makes it an attractive option for these types of activities [2]. For better diagnosis, growth rate forecasting, and treatment planning, data sets are crucial. However, because to the severe partial volume impact, significant heterogeneity in tumour shapes, and imaging conditions, particularly for gliomas, automating this process is difficult [3]. Gliomas and Meningiomas are the most common types

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of primary brain tumors. A glioma is a tumor that forms in the brain or spinal cord. Malignant gliomas are categorized using the labels "low-grade" and "high-grade" depending on how rapidly the tumors spread. It becomes essential to employ computer-assisted methods to overcome these constraints. However, more work needs to be done to more accurately categorise these multiple class malignant tumors [4]. The use of computer assisted methods is necessary to get over these restrictions. In medical image processing, the initial procedure is preprocessing. In the way, various filters are used in this process. One of the filters is a Gaussian filter, which smooths the image or signal by averaging the neighboring values based on a Gaussian distribution [5]. It has blurred edges because it averages the neighboring values. Its aim is only to remove the blurry images, but further noises are not determined in this process. Because an effective filter is employed is essential. Additionally, it preserves edges better than some uniform filters, but not as effectively as the median filter. So, in this work, an efficient filter of the Median filter is used to overcome these drawbacks [6]. Next, the procedure is the segmentation process. Adaptive thresholding, Otsu's method, edge-based and region-based segmentation, and clustering methods are employed in preview works. The thresholding technique is split into two types: local thresholding and global thresholding. In local thresholding, it requires significant computational resources and time. High-resolution images or videos add to the computational cost, making real-time processing challenging. Therefore, in this work, one of the best thresholding processes of global thresholding is utilized. Global thresholding is served as a preprocessing step for more complex image processing tasks. So alternative techniques might be more suitable for images in greater complexity or where precise segmentation is needed [7]. After that, feature extraction is a process in image processing used to transform raw data into a set of meaningful and useful features or attributes. These features are used to identify patterns, classify data, or perform further analysis. In the context of images, feature extraction aims to represent relevant characteristics of the image in a lower-dimensional form, which is easier to process while retaining essential information. In this way, the HOG technique is used to extract the features accurately. Additionally, it is designed to capture shape information, which is particularly useful for detecting images with well-defined boundaries. The numerous traditional and hybrid ML models were created and carefully analysed to categorise the photos of brain tumours without the use of any human involvement. Therefore, many classification techniques from ML and DL are utilized to rapidly recognize the tumor [8]. Numerous ML techniques have been employed, most of which concentrate on the distinction between benign and malignant tumors or the classification of imaging modalities into two groups. ML techniques such as Random Forest, Decision Tree, and Support Vector Machine (SVM) help with the detection and classification of the tumors. This technique causes a time delay, and poor-quality data leads to inaccurate predictions and misguided insights. There are certain drawbacks to ML. Therefore, DL is mostly employed for difficult tasks, so this work uses a DL algorithm [9]. A correct identification of a brain tumour can be crucial for initiating the right treatment, which eventually lowers the patient survival percentage [8]. An innovative DL-based technique for Glioblastoma Multiforme (GBM) patients' Overall Survival (OS) prediction that can extract tumour genotype-related variables from brain data and include them into OS prediction. A deep transfer learning model is trained and evaluated using three alternative optimisation strategies [10].

An efficient brain cancer detection method built on the foundation of DL techniques employs Convolution Neural Networks (CNN) to generate appearance and spatial accuracy results. It is crucial for assisting radiologists and physicians in detection of brain tumours. An accuracy of the present techniques has to be improved for effective treatments. In this work, the following contributions are achieved:

- To enhance the quality and remove the noise of the image, employ a median filter.
- To extract the features for image detection, and recognition quickly and accurately by using the HOG technique.
- To develop a global thresholding approach for accurate brain tumor segmentation from multimodal MRI.
- To evaluate the accuracy by using a Deep Convolutional Neural Network (DCNN) based model.

In this paper proposes a DL method to identify brain cancers using MRI scans. The following list shows the order in which the paper is presented: Most recent work is covered in Section II. The proposed work is covered in full in Section III. In Section IV, the results are displayed. It contains a conclusion in Section V.

2 Recent Works

Mohamed Wageh *et al* (2024) [11] have presented a deep CNN model and a Computer-Aided Detection (CAD) system to brain cancer detection. Extracts deep features from brain MRI images employing a connection of deep CNN, ResNet-101, DenseNet-201, and VGG-16. These characteristics are then combined and processed through a genetic algorithm to identify the most significant characteristics. Its performance is significantly improving as a consequence, reaching an impressive accuracy. Furthermore, it is essential to refine the technique to enhance its capacity to accurately classify distinct forms of brain tumors.

Md Ishtyaq Mahmud *et al* (2023) [12] have developed a deep learning model for the early detection of brain cancer. It reduces computational costs and achieves the highest performance and classification accuracy in the short amount of time. CNN's several layers and the computer's poor GPU made for a laborious training process. The performance estimate, however, is possible biased because the testing set is non typical of the whole set of information. But when the number of layers or parameters rises, problems like disappearing gradients begin to appear.

Thavavel Vaiyapuri *et al* (2023) [13] have proposed an Ensemble Learning-Driven Computer-Aided Diagnosis Model for Brain Tumor Classification (ELCAD-BTC) technique on MRIs. It identifies and categorizes different stages of brain tumors and MRI noise reduction

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and contrast enhancement using the Gabor Filtering (GF) method. For the precise brain cancer classification performance, the ELCAD-BTC method is needed for three-dimensional MRI in the future. The vanishing gradient problems make training a deeper network more complex, and at a certain depth, accuracy continues to drastically decline.

Hafiz Muhammad Tayyab Khushi *et al* (2023) [14] have presented an EfficientNetB7 technique for improved multi-class brain tumors. It identifies cancers more precisely and effectively and produces the best outcomes in terms of validation accuracy. However, in domains such as medical imaging, gathering a substantial amount of annotated data is often impractical and unavailable. The downside of this system is the absence of segmentation of the tumor region, so further research is needed.

Muhammad Rizwan *et al* (2022) [15] have developed a Gaussian Convolutional Neural Network (GCNN) for detecting and categorizing of brain cancer. It improves its portability and ease and broadens its use in future clinical applications. Additional procedures are necessary to restrict the tumor, so an effective technique is needed to be repeated with larger-scope datasets that include a variety of other factors.

3 Proposed Work Explanation

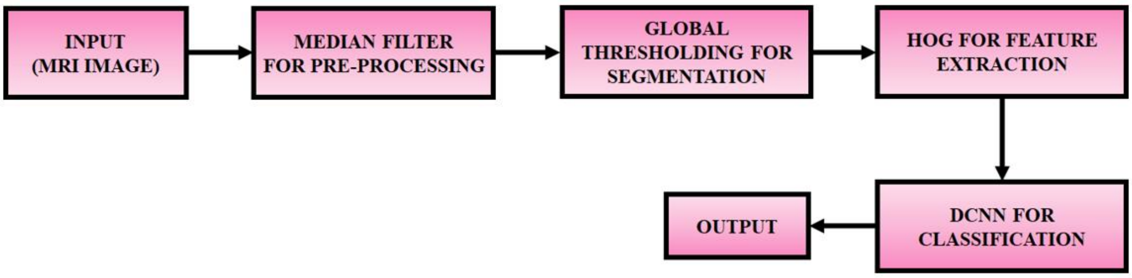

Figure 1: *Block Diagram for Proposed System*

This proposed work uses a deep convolutional neural network method to detect the brain cancer. Figure 1 displays the proposed system's block diagram. The initial stage of preprocessing allows an analysis of the input image by using the Median filter, which works to remove noise and enhance the visibility of blurred images. Global thresholding handles the segmentation step for this modulus after preprocessing. This image segmentation technique classifies pixels based on their intensity values. For the segmented image, the following feature extraction process. The HOG technique extracts the features for image detection and recognition quickly and accurately. Then, the DL classifier technique is allowable. The DCNN classifier is made up of three different types of layers. The segmented picture is subjected to the first convolutional layer in order to extract features. The fully connected layer on the third layer provides the final prediction, and the second pooling layer samples the image to expedite processing. Additionally, the DCNN classification provides excellent specificity and sensitivity for classifying images as having or without cancer. The final step is producing the output image.

3.1 Pre-processing

Preprocessing is the first part in the image processing process. Preprocessing is the collection of methods used on unprocessed data or pictures before to conducting additional analysis or processing operations, like segmentation, classification, or feature extraction. In order to ensure that the following analysis produces more accurate and significant results, the primary objectives are to increase data quality, enhance significant characteristics, and eliminate noise or inconsistencies. Preprocessing improves image quality, lowers noise, and increases the efficiency of later processes like feature extraction or segmentation in the context of MRI imaging. Numerous filter types are employed in this procedure, and for the best image quality, one of the median filter's effective filters is used in this work.

3.2 Median Filter

A nonlinear digital filtering method called a median filter is frequently used to cut down on noise in a signal or image. Among the various window operators available, such as the mean, max, and mode filters, it is among the best. Particularly valuable in remote sensing and medical imaging (e.g., MRI, CT scans) that maintaining edges while lowering noise is crucial. Every pixel in the image is filtered one by one by the median filter, and its neighboring pixels are utilized to determine whether or not that pixel is indicative of its surrounds. Typically, the median filter replaces a pixel value with the median of its nearby values rather than the mean of those values. In contrast to a basic averaging filter, which blurs the image, the median filter preserves the image's edges while eliminating noise. Additionally, it keeps the edges intact while cutting down on noise and it preserves structural information while reducing noise in MRI data.

3.3 Image Segmentation

Segmentation aims to modify or simplify an image's representation, making it easier to understand and analyze. Each segment typically contains pixels that are similar according to certain characteristics, such as intensity, color, texture, or boundaries. Accordingly, the thresholding technique is employed for separating pixels based on intensity values and converting grayscale images into binary ones.

3.4 Global Thresholding

Global thresholding is often a first step in more complex MRI image processing pipelines where regions are relatively homogenous in intensity. In techniques used to classify pixels into different regions (e.g., background and foreground) based on their intensity values. It involves selecting a single intensity threshold that applies to the entire image, and all pixels are compared against this threshold to determine whether they belong to one region or another.

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In a 2D image, a pixel is represented by the notation $f(x, y)$, where x and y stand for the respective horizontal and vertical coordinates. A global threshold is an individual T threshold that is applied to each pixel in an image. If $f(x, y) \geq t$, the point (x, y) is referred as an image pixel; if not, it is referred to as a background pixel. Given below is the segmented image $g(x, y)$:

$$g(x, y) = \begin{cases} 1, & \text{if } f(x, y) < t, \\ 0, & \text{if } f(x, y) \geq t, \end{cases} \tag{1}$$

The procedure described above is known as global thresholding when t is a constant that is applied to the whole image.

3.5 Feature Extraction

Feature extraction is a vital step in processing MRI images, enabling precise analysis and accurate diagnosis in medical applications. Feature extraction is the process of identifying and extracting important information or characteristics from raw data, such as images, signals, or text, to reduce the data's complexity and make it easier to analyze. In the context of image processing, particularly in MRI images, feature extraction is used to highlight relevant structures, patterns, or statistical properties, enabling further tasks like classification, segmentation, or anomaly detection. Therefore, Histogram of Oriented Gradients (HOG) is used in this work. In extracts gradient orientation histograms to capture shape and structural features in the image.

3.6 Histogram of Oriented Gradients (HOG)

HOG remains a widely used feature extraction method in vision-based systems, particularly for tasks involving the detection of images based on their shape and structural properties. HOG captures the structure and appearance of images within an image by focusing on the distribution of edge directions (gradients), making it particularly useful for tasks like human detection, vehicle recognition, and other shape-based detection problems. Within each cell, a histogram is created that accumulates the gradient magnitudes for each orientation bin. This histogram reflects the distribution of edge directions within the cell. By normalizing the gradient histograms, HOG features are less sensitive to variations in lighting conditions and contrast.
The proposed approach employed a greater number of histogram bins on various image regions in order to extract HOG characteristics. The input image was first made into a grayscale image by scaling it to 64 × 128 pixels. Equations (2) and (3) are used to determine the gradient for each pixel in the image.

$$d_x = I(x + 1, y) - I(x, y) \tag{2}$$

$$d_y = I(x, 1 + y) - I(x, y) \tag{3}$$

After that, the gradient orientation, θ, is obtained employing equation (4).

$$\theta(x, y) = \tan^{-1} \frac{d_y}{d_x} \tag{4}$$

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where $I(x, y)$ is the pixel value at (x, y) location and d_x and d_y are the horizontal and vertical gradients, correspondingly.

3.7 Classification

Image classification is a fundamental task used in applications like object detection, facial recognition, medical image analysis, and many others. The goal of image classification is to train a model to recognize patterns, textures, shapes, and features in the image to correctly classify it into predefined categories.

3.8 Deep Convolutional Neural Network (DCNN)

Convolutional Neural Networks (CNNs) are widely used to image classification as they are specifically designed for working with image data and excel at feature extraction and classification. DCNNs are an extension of traditional (CNNs), with multiple layers of convolution, pooling, and fully connected layers stacked deeper in the architecture to capture increasingly complex patterns from input data. The convolution layer, pooling layer, fully connected layer, dropout layer, and activation layer are its five layers.

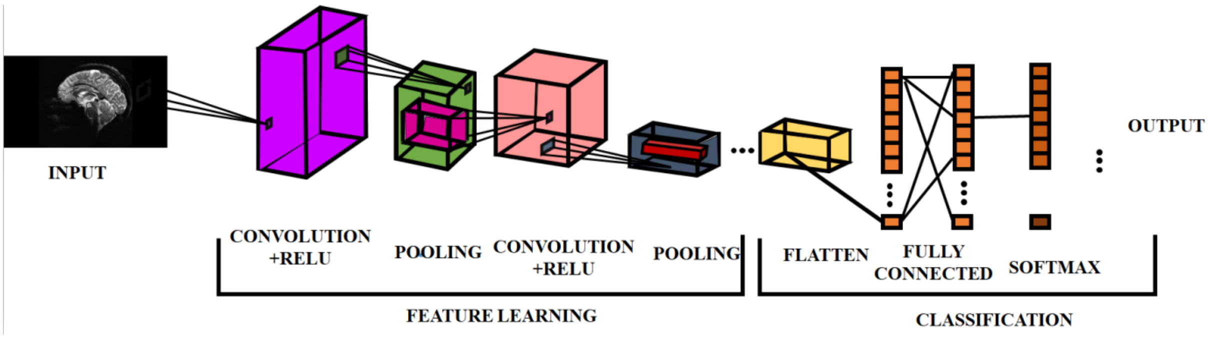

Figure 2: *DCNN Architecture*

Convolutional Layer

The initial layer in the process of extracting different features from the input photos is this one. The convolutional mathematical process is carried out in this layer between the input image and a filter with a specific size of MxM. Afterwards, further layers receive this feature map in order to learn additional features from the input image.

Pooling Layer

Typically, a convolutional layer is followed by a pooling layer. In max pooling, the greatest segment of the feature map is utilized. Average pooling calculates the average of the constituents in an Image segment of a given size. The entire sum of the components in the designated segment is estimated by sum pooling.

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Fully Connected Layer

An input vector comprising the image's flattened pixels, which have been filtered, adjusted, and reduced by the convolution and pooling layers, is received by fully connected layers. The chance that an image is going belong to a particular class, such as whether or not it is a tumor, is then determined by applying the SoftMax function to the output of the fully connected layers.

Dropout

Once all features in the training dataset are connected to the fully connected layer, overfitting usually occurs. The size of the final model is decreased during training by removing certain neurons from the neural network using a dropout layer.

Pooling Layer

Finally, one of the most important parameters of the CNN model is the activation function. They are used in the process of learning and estimating continuous, complex interactions between several types of network variables. SoftMax is utilized for multi-class classification, and sigmoid and SoftMax functions are favoured for a CNN model used for binary classification.

4 Results and Discussion

In this research, the system established its robustness in successfully diagnosing brain cancer even with the image sizes decreasing by more than half of their original sizes. This is explained by the fact that the fusions of features extracted by HOG and DCNN yielded a greater number of unique features. Additionally, the work done using a Python Jupyter software program to identify brain cancer and the outcomes are covered below.

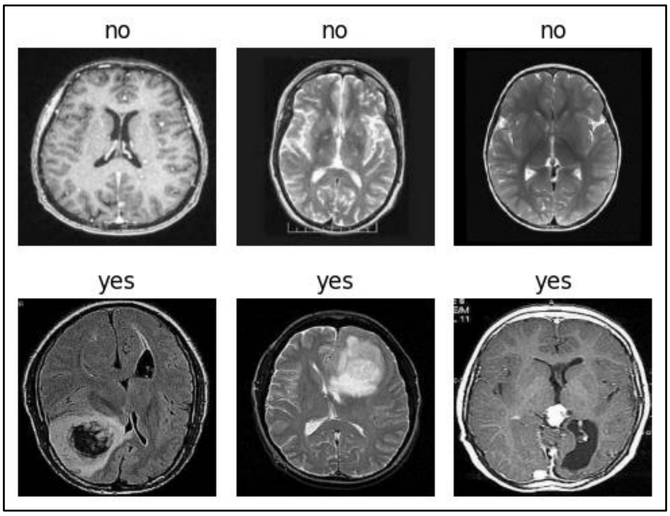

Figure 3: *Input Image*

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Figure 3 displays the input image dataset of the brain. Additionally, the supplied image is in grayscale. The database contains images of both normal and abnormal brain tumors. Images of both normal and pathological diseases are included in the database. One of the images is selected as the input.

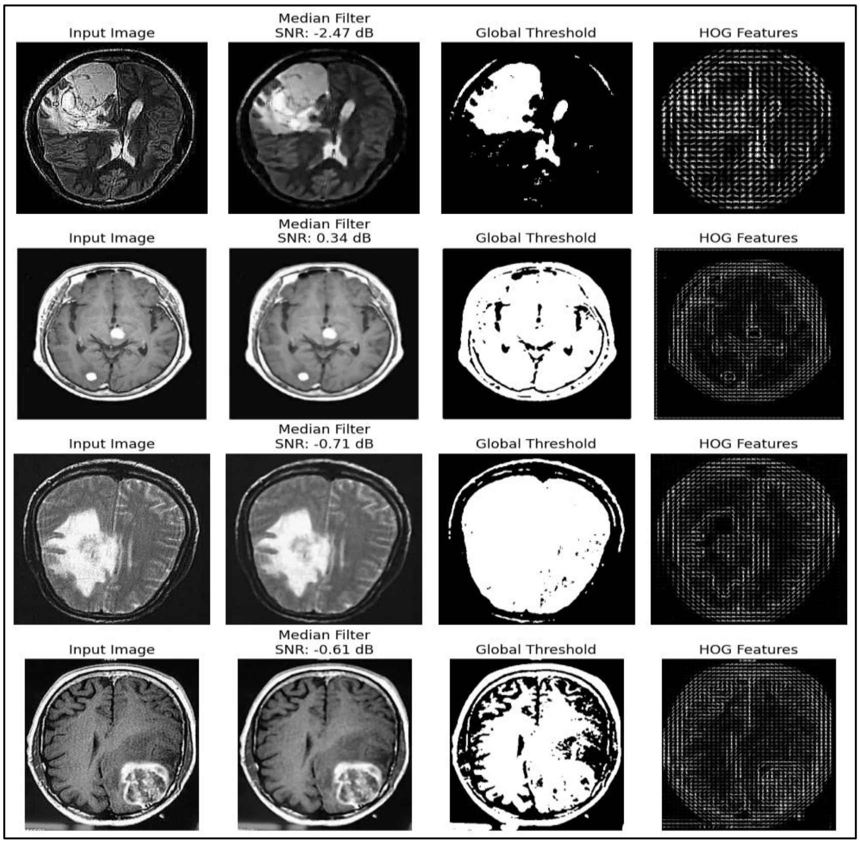

Figure 4: *Segmented Images*

Figure 4 illustrates the segmented images in various input image. The input images appear in the first rows after being pre-processed using the Median filter, whose results are displayed in the second rows. The segmented images are then placed in the third rows once the segmentation method is applied. Following that, the HOG methodology offers an effective technique for extracting the features from the images that are in the last row during the feature extraction and noise removal phase.

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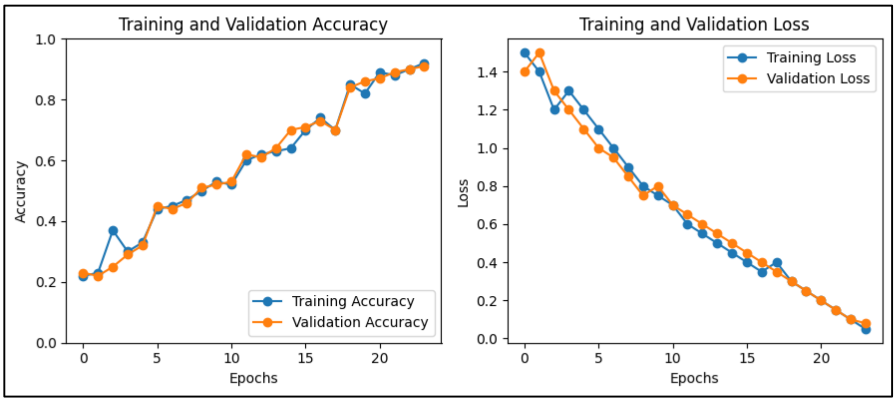

Figure 5: *Model Accuracy and Model Loss*

Demonstrations of the model's accuracy and loss are presented in Figure 5. In the figure, there is clear evidence of accuracy curves and losses of training and validation, respectively. This indicated that compared to single feature extraction methods, the proposed technique could classify brain cancer more accurately.

Table 1: *Comparison performance of various classifications*

CLASSIFICATION	ACCURACY	PRECISION	LOSS
SVM [2]	85.8%	53.4%	0.75%
KNN [4]	88.43%	79%	0.43%
DCNN [Proposed]	91.23%	90.39%	0.28%

The accuracy, precision values of the proposed method, along with other methods, is illustrated in Table 1. After comparing the proposed approach with various algorithms, results demonstrate that the proposed model performs better for classification than the other methods. Additionally, the loss for the proposed method is reduced.

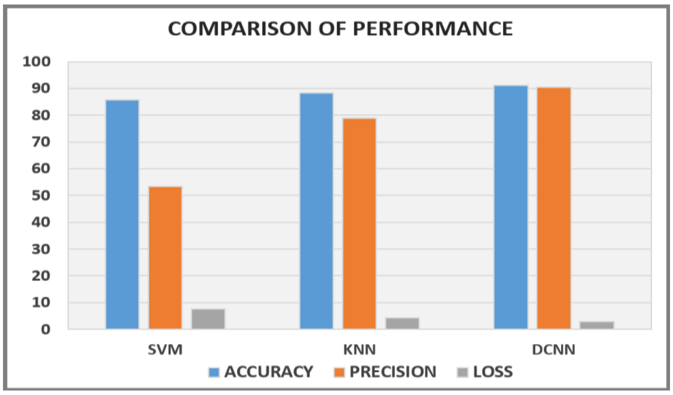

Figure 6: *Comparison of Performance*

The performance of the proposed DCNN classification and a comparative graph of several classes are shown in Figure 6. Alternative classifications with accuracy and loss values, such as SVM and KNN, have been observed. The proposed approach demonstrated the highest level

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of performance in identifying brain tumors, achieving a validation accuracy of 91.23% and precision of 90.39%.

5 Conclusion

This paper provides an accurate detection of brain cancer based on Deep learning technique. This paper is analyzed from the input image, the image preprocessing methods employed, and the color cropped method in accordance with the inclusion criteria and quality evaluation. Accurately detecting brain cancer is made possible by the segmentation approach, HOG feature extraction, and DCNN classification employed in this work. The affected type of disease is successfully identified using these methods. This information aids in deciding upon the most effective course of therapy for medical treatment. It helps monitor the effectiveness of treatment and inform future management decisions. Moreover, the proposed method outperforms existing models and has good accuracy. This highlights the efficacy of the proposed approach and the possibility of DL for MRI-based rapid brain tumor diagnosis.

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