10.48047/jocaaa.2025.34.06.5

# Deep Learning-based System for Brain Tumor Detection and Localization on MRI Scans: A Systematic Review

**Jharna Chopra[1], Rajesh Mahule[2]**
[1]Research Scholar, Department of IT, Guru Ghasidas Vishwavidyalaya (Central University), Bilaspur, India, Jharna.chopra@gmail.com
[2]Associate Professor, Department of IT, Guru Ghasidas Vishwavidyalaya (Central University) Bilaspur, India, rmahule71@gmail.com

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***Abstract***

*Magnetic Resonance Imaging (MRI) has become a cornerstone in the analysis of brain structures and the detection of tumors, offering detailed images of soft tissues. However, the variability in tumor size and shape poses a significant challenge for radiologists in accurately identifying and classifying these abnormalities. To address this, researchers have leveraged recent advancements in brain tumor detection using machine learning and deep learning techniques, while also exploring the availability of public datasets and the challenges associated with this field. The objective of this study is to review the existing work done in this field and identify the challenges to guide future research efforts toward developing effective decision support systems that improve the diagnostic accuracy of radiologists.*

***Key Words**: Brain Tumor Detection, Machine Learning, Deep Learning, Segmentation, Classification, Magnetic Resonance Imaging (MRI).*

## 1. Introduction

A brain tumor is the growth of abnormal cells within the brain, leading to increased intracranial pressure and disruption of brain function. Tumors are categorized as either benign (non-cancerous) or malignant (cancerous). Malignant tumors can invade nearby tissues, making their early identification and classification essential for effective treatment and patient survival.

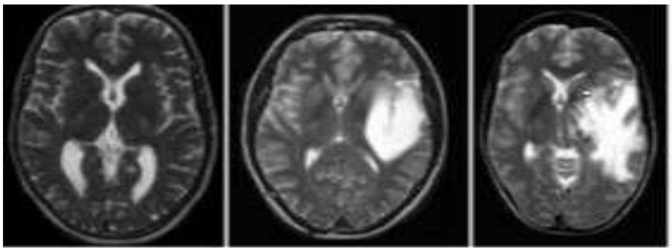

**Figure 1: MRI image of Normal Brain, Benign Tumor, Malignant Tumor respectively [53]**

Several imaging modalities—such as Computed Tomography (CT), Positron Emission Tomography (PET), and MRI—are employed to detect brain tumors. Among them, MRI stands out as a non-invasive method that uses magnetic fields and radiofrequency signals to visualize brain structures. Common MRI sequences used for tumor detection include T1-weighted and T2-weighted. Current recommendations for brain tumor MRI protocol include the following sequences: 2D T1-weighted imaging (T1WI), fluid-attenuated inversion recovery (FLAIR) 2D axial, axial susceptibility-weighted imaging (SWI), DWI 2D axial, 3D T1 post contrast.

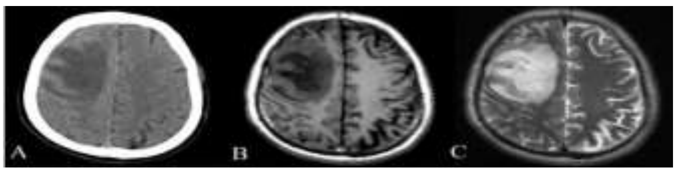


**Fig-2:** CT scan of the brain B) T1-weighted MRI scan of the same brain C) T2-weighted MRI scans of the same brain

Detecting tumors in MRI scans is challenging due to the intricate nature of the images, making it difficult for radiologists to identify subtle irregularities. To improve diagnostic accuracy, researchers from computer science field have introduced Machine Learning (ML)-driven Computer-Aided Diagnosis (CAD) systems that provide valuable support in

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medical decision-making. This survey reviews different ML and DL approaches for brain tumor segmentation and classification, outlining their advantages and drawbacks.

The rapid advancements in machine learning (ML) and deep learning (DL) have positioned these technologies as vital tools in brain tumor detection and classification, particularly within MRI imaging. Despite this progress, there remains a need for a comprehensive survey that evaluates the effectiveness, challenges, and practical applicability of various ML and DL techniques specifically tailored to brain tumor segmentation and classification. This survey seeks to address this gap, providing a resource that outlines the current landscape, identifies limitations, and highlights areas where further research is essential for developing robust decision support systems in medical diagnostics.

To conduct this survey, we systematically reviewed recent studies focusing on ML and DL applications in brain tumor detection. Key stages, including preprocessing, segmentation, feature extraction, and classification, were examined across diverse methodologies. Each technique was assessed based on its performance and accuracy.

## 1.2. Machine Learning Techniques For Brain Tumor Detection

Machine learning-based brain tumor detection involves four primary stages: **Preprocessing**, **Segmentation**, **Feature Extraction**, and **Classification**.

***A. Preprocessing***

In medical imaging, obtaining accurate and clear images is essential for reliable diagnosis. The quality of medical images is influenced by factors such as the imaging modality used, including MRI, PET, and CT scans. MRI images, in particular, often contain unnecessary components and are affected by **Rician noise**, which depends on the signal and is difficult to eliminate. Image preprocessing techniques, such as filtering, contrast enhancement, and skull stripping, are employed to preserve the original image quality and eliminate irrelevant artifacts.

- Filtering: Techniques such as Gaussian and median filtering are used to reduce noise while preserving essential image details.
- Contrast Enhancement: Techniques like Histogram Equalization and Contrast-Limited Adaptive Histogram Equalization (CLAHE) are employed to improve tumor visibility.

***B. Segmentation***

Segmentation is the process of isolating the Region of Interest (ROI) from medical images. In brain tumor detection, it involves separating the tumor region from healthy brain tissue in MRI scans. Both supervised and unsupervised methods are applied for segmentation, including thresholding, soft computing techniques, atlas-based methods, clustering, and neural networks. Thresholding techniques encompass adaptive, global, Otsu's, and histogram-based approaches. Unsupervised clustering algorithms, such as **K-means** and **Fuzzy C-means**, effectively partition brain MRIs into **Gray Matter (GM)**, **White Matter (WM)**, and **Cerebrospinal Fluid (CSF)**. Additionally, bio-inspired algorithms like **Particle Swarm Optimization (PSO)** and **Genetic Algorithms (GA)** have been used. Recent advances highlight that deep learning models such as **CNNs**, **Mask-RCNN**, and **U-Net** outperform traditional segmentation techniques.

***C. Feature Extraction***

Feature extraction focuses on deriving relevant attributes from MRI images, such as shape, texture, and wavelet features. A widely adopted method for texture analysis is the **Gray-Level Co-occurrence Matrix (GLCM)**, which captures second-order statistical features like energy, correlation, and contrast. **Wavelet features** are extracted using the **Discrete Wavelet Transform (DWT)**, which decomposes the raw image and selects approximation coefficients as feature vectors. A combination of handcrafted features and deep learning-generated features, utilizing models like **CNNs**, **ResNet**, and **Capsule Networks**, has demonstrated promising results. Techniques such as **Principal Component Analysis (PCA)** and **Genetic Algorithms (GA)** are used to reduce the dimensionality of the feature space.

***D. Classification***

Brain tumors are primarily categorized into two groups: benign and malignant tumors. Malignant tumors can be further classified into specific types, including Glioma, Meningioma, and Pituitary tumors. The World Health Organization (WHO) has established a grading system for Gliomas, which includes four distinct grades, as illustrated in Fig-3.

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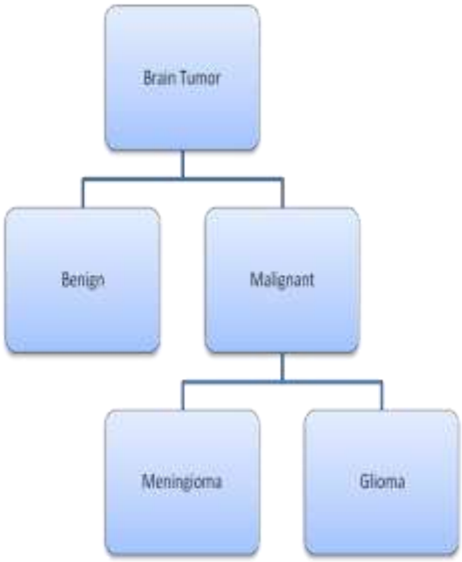


**Figure3: Brain Tumor Classification**

The remaining part of the paper is organized as follows: Section 2 illustrates related works to this survey and shows various comparisons of various approaches based on their accuracy, computational and efficiency.

## 2. LITERATURE REVIEW

There are various classifications of ML approaches used for brain tumor detection. The table below provides a structured overview of machine learning techniques in brain tumor detection, categorized by purpose and specific methodologies.

**Table 1: The classification of ML approaches used for brain tumor detection**

| Category | Description | Examples of Techniques |
|---|---|---|
| **Image Preprocessing and Enhancement-Based Methods** | Focuses on improving MRI image quality to enhance analysis accuracy. Methods involve filtering and contrast adjustments to reduce noise and improve feature visibility | Gaussian-blur-based sharpening, Contrast-Limited Adaptive Histogram Equalization (CLAHE) |
| **Segmentation-Based Techniques** | Aims to isolate tumor regions from MRI scans for focused analysis. Techniques range from traditional methods to advanced deep learning for higher precision | Thresholding, K-means Clustering, Fuzzy C-means, Genetic Algorithms (GA), Particle Swarm Optimization (PSO), CNN, U-Net |
| **Feature Extraction Methods** | Involves deriving relevant image features, such as shape and texture, which aid in classification accuracy. Uses statistical and wavelet-based methods for detailed feature extraction | Gray-Level Co-occurrence Matrix (GLCM), Discrete Wavelet Transform (DWT), Handcrafted and CNN-based features |
| **Classification Models** | Focuses on distinguishing between tumor types and grades. Classification methods include traditional ML algorithms and advanced DL architectures for high accuracy. | Support Vector Machines (SVM), Random Forest, CNN, Recurrent Neural Networks (RNN), Transfer Learning (ResNet, GoogLeNet) |
| **Hybrid and Ensemble Approaches** | Combines multiple techniques to leverage individual model strengths, often yielding higher accuracy and robustness. These approaches are particularly useful for complex classification tasks | SVM with GA, CNN with Bayesian Methods, Ensemble Learning Models |
| **Generative Models** | Addresses data scarcity by generating synthetic MRI images for training, enhancing model robustness and reducing over fitting in datasets | Generative Adversarial Networks (GANs) |

In [1] the authors Rasheed et al.have developed a novel brain tumor classification method by combining Gaussian-blur-based sharpening and Contrast-Limited Adaptive Histogram Equalization (CLAHE) techniques with a Convolutional Neural Network (CNN). This approach demonstrated an impressive accuracy of 97.84% in categorizing different brain tumor types. Although the method showed promising results, it may not be suitable for real-time data processing due to its computational requirements. In [2] the authors Asiri et al. have proposed a multi-level Generative Adversarial Network (GAN) to extract robust features and learn the fundamental structures of MRI images for distinguishing between four brain tumor classes. Their method achieved an accuracy of 96%, which is expected to contribute to the generation of realistic medical image data, thereby enhancing the training of medical experts for predicting acute diseases.In [3] the authors Ekong et al. have developed a Bayesian-CNN model for brain tumor classification by

10.48047/jocaaa.2025.34.06.5

integrating deep learning and Bayesian methods. Their approach achieved an accuracy of 94.38% and was deemed suitable for real-life scenarios, although it did not utilize a three-dimensional MRI system.In [4] the authors Almalki et al. have proposed a hybrid approach that combined Speeded Up Robust Feature (SURF) extraction, k-means clustering, and Gaussian and nonlinear techniques to automatically detect brain tumors from MRI images. Their method achieved an accuracy of 95.33% with high speed and lower computational time.In [5] Das et al. the author developed a convolutional neural network (CNN) to classify brain tumors into three categories: glioma, meningioma, and pituitary. The proposed approach achieved an accuracy of 94.39%. However, the model had a high number of parameters and was trained on a relatively small dataset, which could limit its generalization capabilities.In [6] the authors Khawaldeh et al. proposed a research is on non-invasive grading of gliomatumors using Magnetic Resonance Imaging (MRI) with Convolutional Neural Networks (CNN). The study aims to accurately classify images of brain tumors using a ConvNet model with a dataset of 130 images from the Cancer Imaging Archive, achieving an accuracy of 91.16%.In [7] the authors Preethi et al. combined wavelet texture features with a Deep Neural Network (DNN) for tumor detection and segmentation over MRI images. Their research presents an efficient MRI tumor classification and segmentation process based on multiple stages, achieving a maximum accuracy of 92% for the classification of different types of tumorsIn [8] the authors Kang et al. conducted a study on MRI-based brain tumor classification using an ensemble of deep features and machine learning classifiers. Their research aimed to enhance brain tumor classification accuracy by combining deep features and machine learning techniques. This approach involved extracting deep features from MRI images using pre-trained convolutional neural networks (CNNs) and then combining these features with machine learning classifiers to achieve state-of-the-art performance for brain tumor classification.In [9] the authors Deepak et al. explored brain tumor classification using deep CNN features via transfer learning. Their research leveraged the concept of deep transfer learning and pre-trained GoogLeNet to improve brain tumor classification accuracy, achieving an accuracy of 98%. This approach demonstrated the potential of deep learning techniques in enhancing the accuracy of brain tumor classification. In [10] the authors Kharrat et al. presented a hybrid approach for the automatic classification of brain MRI using Genetic Algorithm (GA) and Support Vector Machine (SVM). Their research aimed to develop a technique using wavelet transform, GA, and SVM for classifying brain MRI images, achieving an accuracy of 98.14%. This method highlighted the advantages of combining different techniques for brain tumor classification, including accuracy, robustness, non-invasiveness, and cost-effectivenessIn [11] the authorsVaruna et al. conducted a study on the identification and classification of brain tumor MRI images using feature extraction with Discrete Wavelet Transform (DWT) and a Probabilistic Neural Network (PNN) classifier. The research aimed to classify brain tumors accurately and efficiently, achieving an accuracy of 95%. The proposed method was noted to be fast and accurate, but it did not consider real-world clinical-based brain tumor MRI images.In [12] the authorsNoreen et al. proposed a model for feature extraction and classification of brain tumors using deep learning and machine learning models, including InceptionV3, Xception, softmax, SVM, Random Forest, and K-Nearest Neighbours. The ensemble method was used to combine the predictions of these models, achieving an accuracy of 94.34% and outperforming existing models.In [13] the authors Rasheed et al. presented an automated classification of brain tumors from Magnetic Resonance Imaging (MRI) using deep learning techniques. The researchers employed Gaussian-blur-based sharpening, Contrast-Limited Adaptive Histogram Equalization (CLAHE), and Convolutional Neural Networks (CNNs) to accurately classify various types of brain tumors, such as glioma, meningioma, and pituitary tumors, achieving an accuracy of 98.04%. However, the method was not suitable for real-time detection systems.In [14] the authors Swaraja et al. conducted a study on brain tumor classification using deep Convolutional Neural Networks (CNNs). The researchers applied transfer learning on pre-trained models, including AlexNet, ResNet-50, and VGG-16, to classify brain tumors.

The proposed approach achieved an accuracy of 98.28%. Although the models demonstrated high accuracy and less computational time, they did not provide in-depth classification details.In [15] the authors Saeedi et al. presented an MRI-based brain tumor detection method using convolutional deep learning techniques and machine learning approaches. The researchers employed 2D CNN and auto-encoder networks to classify brain tumors, achieving an accuracy of 96.47% and 95.63%, respectively. The proposed method was noted to have optimal execution time, but the details on its performance in real-world scenarios were not provided.In [16] the authors Abdusalomov et al. proposed a deep learning-based approach for brain tumor detection using Magnetic Resonance Imaging (MRI). The researchers employed the YOLOv7 (You only look once) object detection model to detect the existence of brain tumors and pinpoint their precise location within the MRI images. The proposed method achieved an accuracy of 99.5%, demonstrating its effectiveness in brain tumor detection. However, the study did not address the complexities of real-world diagnostic scenarios.In [17] the authors Anaraki et al. conducted a study on the classification and grading of glioma brain tumors using Magnetic Resonance Imaging (MRI) and a combination of Convolutional Neural Networks (CNNs) and Genetic Algorithms (GAs). The proposed algorithm classified various grades of glioma and two other widespread tumor types with high precision, achieving an accuracy of 94.2%. However, the method performed poorly with large datasets.In [18] the authors Ravinder et al. introduced an enhanced brain tumor classification approach using a Graph Convolutional Neural Network (GCNN) architecture. The researchers leveraged the spatial and structural information of brain MRI images to improve the classification of different brain tumor types. The proposed method demonstrated promising

10.48047/jocaaa.2025.34.06.5

results, but the details on its performance and applicability in real-world scenarios were not provided.In [19] the authors Liu et al. presented a comprehensive survey on the applications of deep learning to Magnetic Resonance Imaging (MRI) images. The review covered various deep learning techniques, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Generative Adversarial Networks (GANs), and their use in medical image analysis tasks such as segmentation, classification, and detection.In [20] the authors Mehrotra et al. explored a Transfer Learning approach for AI-based classification of brain tumors using Magnetic Resonance Imaging (MRI) data. The researchers utilized pre-trained Convolutional Neural Network (CNN) models, including AlexNet, GoogLeNet, ResNet50, ResNet101, and SqueezeNet, to classify MRI images of brain tumors into benign and malignant types. The proposed method achieved an accuracy of 99.04%, but it was noted to be less suitable for large datasets.In [21] the authorsTummala et al. conducted a study on the classification of brain tumors from Magnetic Resonance Imaging (MRI) using Vision Transformers Ensembling. The researchers employed a novel approach that combined the capabilities of Vision Transformers (ViT) with ensemble learning to accurately classify brain tumors. The proposed method achieved an accuracy of 99.5%, demonstrating its effectiveness in brain tumor classification. However, the study did not address the complexities of real-world diagnostic scenarios.In [22] the authors Khan et al. presented an accurate brain tumor detection method using deep convolutional neural networks (CNNs). The researchers utilized a pre-trained CNN model and fine-tuned it on a dataset of brain MRI images to detect brain tumors. The proposed method achieved an accuracy of 99.5%, outperforming existing methods. However, the study did not provide details on the applicability of the method in real-world scenarios.In [23] authors Gudigar et al. explored the application of multi-resolution analysis for automated detection of brain abnormalities using MRI images. The researchers compared the performance of different multi-resolution analysis techniques, including wavelet transform and curvelet transform, for detecting brain abnormalities. The proposed method demonstrated promising results, but the study did not provide details on its applicability in real-world scenarios.In [24] the authors Shah et al. presented a review of brain tumor segmentation techniques on medical images. The researchers discussed various techniques, including thresholding, edge detection, and clustering, for segmenting brain tumors from MRI images. The review highlighted the challenges and limitations of existing methods and suggested future directions for research.In [25] the authors Hamza et al. conducted a study on the detection of brain tumors using deep learning. The researchers employed a deep learning approach that combined the capabilities of Inception, VGG16, MobileNet, and ResNet to detect brain tumors. The proposed method achieved an accuracy of 99.86%, demonstrating its effectiveness in brain tumor detection. However, the study did not provide details on the applicability of the method in real-world scenarios.In [26] the authors Kumar et al. presented a hybrid approach for classifying brain MRI tumor images. The researchers combined the capabilities of discrete wavelet transform and genetic algorithm to classify brain tumors as benign or malignant. The proposed method achieved an accuracy of 90%, reducing the manual labelling time. However, the study did not provide details on its applicability in real-world scenarios.In [27] the authors Sapra et al. introduced two deep learning models, a "proposed 23-layer CNN" and a "Fine-tuned CNN with VGG16," designed to work with different volumes of image data. Data augmentation techniques were used to enhance the performance of the "Fine-tuned CNN with VGG16" model. The proposed models achieved 97.8% and 100% classification accuracy for the employed datasets. In [28] the authors Seetha et al. employed convolutional neural network (CNN) architecture with data augmentation to improve the classification performance. The model achieved 88.7% accuracy.In [29] the authors Balasooriya et al. proposed a sophisticated CNN model for brain tumor classification, comparing it with other machine learning techniques. The model achieved high accuracy, but the exact figures were not provided.In [30] the authors Saxena et al. proposed two deep learning methods, a new 2D Convolutional Neural Network (CNN) and a convolutional auto-encoder network, for diagnosing three types of brain tumors and healthy brains. Pre-processing and augmentation algorithms were applied to the MRI brain images before training the models. In [31. 32] the authors Chattopadhyay et al. proposed three distinct CNN architectures for brain tumor classification. The first CNN architecture achieved 99.33% accuracy in detecting brain tumors, the second CNN architecture achieved 92.66% accuracy in classifying brain tumors into five types (normal, meningioma, glioma, metastatic, and pituitary), and the third CNN architecture achieved 98.14% accuracy in classifying brain tumors.In [33, 34, 36] the authors Kehar et al. employed a convolutional neural network (CNN) architecture with data augmentation to improve the classification performance. The model achieved 92% accuracy on the test set using SVM machine learning.

10.48047/jocaaa.2025.34.06.5

## Table 2: Comparisons of various classification techniques

| Author | Year | Classification Method | Advantages | Limitation |
|---|---|---|---|---|
| Rasheed*et al.* [1] | 2023 | Gaussian-blur-based sharpening & Adaptive Histogram Equalization using CLAHE | Robust and Accurate | Not suitable for real time data |
| Asiri*et al.* [2] | 2022 | GenerativeAdversarialNetwork (GAN) | Will help the generation of real medical image data to maximize the training of themedical experts for the acute prediction of medical diseases. | - |
| Ekong*et al.* [3] | 2022 | Bayesian-CNN | can be used in real-life scenarios and radiology | three-dimensional system is not adopted |
| Almalk*et al.* [4] | 2022 | Speeded up Robust Feature (SURF) | high accuracy and lower computational time | |
| Das *et al.*[5] | 2019 | CNN | there is a better chance of generalization which keeps the model stable. | The no. of parameters of the model is too high, and the model is trained on a significantly small amount of data |
| Khawaldeh *et al.* [6] | 2018 | CNN | innovative | this study only includes axial FLAIR-weighted MR images. |
| Preethi.*etal*. [7] | 2019 | combining wavelet texture features and a deep neural network (DNN) | maximum accuracy | for the classification of the different types of tumors hybrid technique is not used |
| Deepak *etal.* [9] | 2019 | Concept of deep transfer learning and uses a pre-trained GoogLeNet | Minimum Prepocessing | There was considerable misclassification of samples from the class meningioma |
| Kharrat.et.al [10] | 2010 | genetic algorithm and support vectormachine (SVM) | Accurate, robust, non-invasive, inexpensive | it necessitates fresh training each time whenever there is a change in image database. |
| Varunaet al. [11] | 2018 | probabilistic neural network classifier | Fast & accurate | real- andclinical-based cases were not considered |
| Noreen et al. [12] | 2021 | InceptionV3 Ensemble | outperformed the existing models | |
| Rasheeet al. [13] | 2023 | CNN | High accuracy, generalization capability, execution speed | Not suitable for real-time detection systems |
| Kuraparthi et al. [14] | 2021 | Deep CNN | High accuracy and less computational time | these models do not classify in-depth classification |
| Sanjeevet al. [26] | 2017 | discrete wavelet transform&Genetic algorithm | reduces the manual labeling time | Higer the RMS error rate |
| Hamza et al.[25] | 2022 | Inception, VGG16, MobileNetResNet | High accuracy | - |
| Rajatet al. [20] | 2020 | AlexNet, GoogLeNet, ResNet50, ResNet101, and SqueezeNet | AlexNet performs with best accuracy | Not suitable with large dataset |
| Abdusalomovet al.[16] | 2023 | YOLOv7 | Higher accuracy | Does not address the complexities of real-world diagnostic |
| Saeedi et al.[15] | 2023 | 2D CNN &auto-encoder networks | optimal execution time | - |

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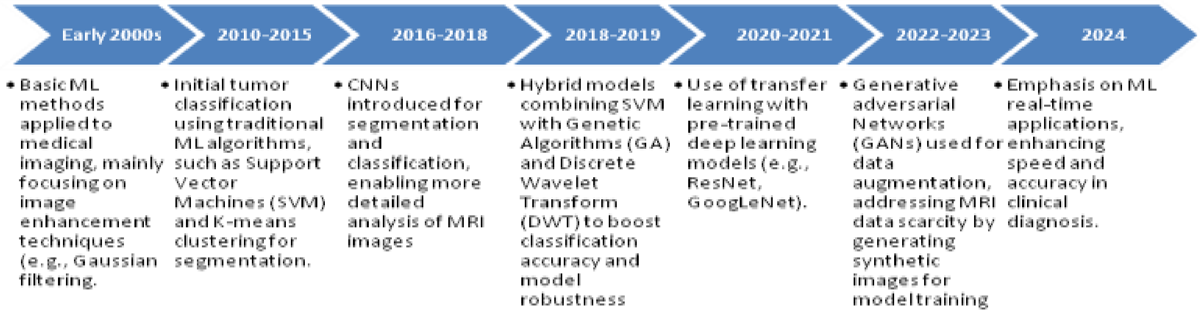


**Fig-3: The evolution from basic machine learning techniques toward multi-stage models.**

## 3. CONCLUSION

Based on the comprehensive review of machine learning (ML) and deep learning (DL) applications in brain tumor detection, it is evident that these technologies offer substantial promise in improving diagnostic accuracy and supporting clinical decision-making. ML and DL models, particularly those leveraging CNNs, GANs, and hybrid approaches, have demonstrated success in tasks such as segmentation and classification of MRI images, providing enhanced detection accuracy. However, challenges remain in the areas of real-time implementation, data availability, and model interpretability. These issues limit the practical applicability of current models in clinical settings.

Future research should prioritize optimizing computational efficiency, refining hybrid models, and expanding the availability and quality of training datasets. Techniques such as synthetic data generation and real-time decision-support systems are essential for bridging the gap between research and clinical use. By addressing these challenges, ML and DL models can further their impact on brain tumor diagnostics, ultimately contributing to better patient outcomes.

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