Brain Tumor Detection Using Deep Learning

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Abstract

Brain tumors, arising from abnormal cell growth in the brain, can be life-threatening without accurate detection and treatment planning. Early detection and accurate classification of brain tumors are crucial for effective treatment planning and improved patient outcomes. Traditional methods like manual MRI examination and rule-based algorithms often lack precision, resulting in inconsistent detection and classification of brain tumors. In this work, the brain tumor detection and classification system is proposed to resolve these problems. This model uses CNN to accurately detect and classify brain tumors into types such as glioma, meningioma, and pituitary tumors. Using a dataset of 7,022 brain MRI images, the model utilizes advanced CNN architectures, including ResNet-50, DenseNet, and EfficientNetB1 for accurate detection and classification of tumors. However, these models tend to suffer from overfitting issues, affecting their generalization capability. To address this, we also employ InceptionV3, which demonstrates superior accuracy and robustness in detecting and classifying brain tumors. Therefore, patients will receive an accurate diagnosis, and the necessary treatment plan will be developed.

Keywords: Brain tumor, deep learning, convolutional neural networks (CNN), Efficient NetB1, ResNet-50, DenseNet, Inception V3.

DOI: https://doi.org/10.5281/zenodo.15285931

1. Introduction

Brain tumors are abnormal growths of cells within the brain that can disrupt essential neurological functions, leading to serious health complications and cognitive impairments. These tumors can be benign or malignant, and their early detection is critical for effective treatment planning, minimizing progression, and improving patient survival rates. Magnetic Resonance Imaging (MRI) is the most widely used imaging modality for brain tumor detection due to its ability to provide detailed images of brain tissues without ionizing radiation.However, traditional MRI-based diagnosis typically relies on manual examination by radiologists, which is time-consuming, labor-intensive, and susceptible to human error or diagnostic inconsistencies, especially in cases involving subtle abnormalities. As a result, there is a growing need for automated and accurate diagnostic systems that can assist medical professionals in identifying and classifying brain tumors efficiently.To address these challenges, the system presents an AI-powered solution utilizing deep learning for automatic brain tumor detection and classification from MRI images. The system leverages the power of Convolutional Neural Networks (CNNs), which are highly effective in extracting spatial hierarchies from visual data. Specifically, models such as ResNet-50, DenseNet, EfficientNetB1, and InceptionV3 are employed to analyze complex patterns within brain scans and distinguish between different tumor types with high precision. These models are trained on a diverse and extensive medical imaging dataset to ensure robustness and generalizability across various cases.Additionally, image preprocessing and enhancement techniques are applied to improve MRI clarity and optimize model input quality, which further boosts classification accuracy. The integration of multiple CNN architectures not only enhances overall system performance but also reduces false predictions, making the model more reliable for practical deployment in clinical settings.

2. Literature Review

Brain Tumor Detection Based on Naïve Bayes Classification uses probabilistic reasoning for binary classification but suffers from low accuracy due to its assumption of feature independence. Despite its simplicity and speed, the model fails to capture complex relationships between MRI features, limiting its effectiveness in real-world diagnostic scenarios [2]. SVM-Based Aphasia Classification applies SVMs to support diagnosis in language-impaired patients, though it struggles with kernel selection and scalability. Additionally, the model's performance heavily relies on proper feature extraction, and its computational cost increases significantly with larger datasets[3].Explainable AI in Brain Tumor Diagnosis highlights the need for interpretability in ML/DL models but notes the trade-off between transparency and performance .The study emphasizes that clinicians prefer understandable models for decision-making, yet the most accurate deep learning systems often behave as black boxes[4].A hybrid approach in Brain Tumor Detection Using Decision Trees and KNN works well on small datasets but overfits on larger ones .While this combination leverages the simplicity of KNN and the interpretability of decision trees, it lacks robustness when faced with noisy or imbalanced data[5].Random Forest-Based Detection reduces false positives through ensemble learning, yet introduces complexity in parameter tuning. The method enhances model stability and reduces variance, but its high number of trees can lead to slower prediction times and increased memory usage [6]. CNN-based models in Multiclass MRI Tumor Classification and MRI Brain Tumor Segmentation Using Random Forests improve multi-type classification and segmentation, but require large labeled datasets and face spatial consistency issues. These models demonstrate state-of-the-art accuracy, yet their dependency on expert-annotated data and high computational demands pose challenges for widespread clinical deployment [7]. All the models, most existing models face challenges related to limited generalization, dependency on large labeled data, and trade-offs between accuracy, interpretability, and computational complexity.

3.1 Proposed System

The proposed system is designed to detect brain tumors accurately and efficiently using deep learning. It processes MRI scan images using powerful models like ResNet50, DenseNet, EfficientNetB1, and InceptionV3. These models use convolutional neural networks (CNNs) to automatically extract features from the images, removing the need for manual analysis. The system not only detects tumors but also classifies them, making it a complete tool for brain tumor diagnosis. The process begins with image preprocessing, where the MRI scans are cleaned and improved. Techniques like normalization, noise reduction, and contrast enhancement are used to make the images clearer and more consistent. Data augmentation methods such as rotation, flipping, and scaling help the model handle a wide variety of image types, improving its performance.

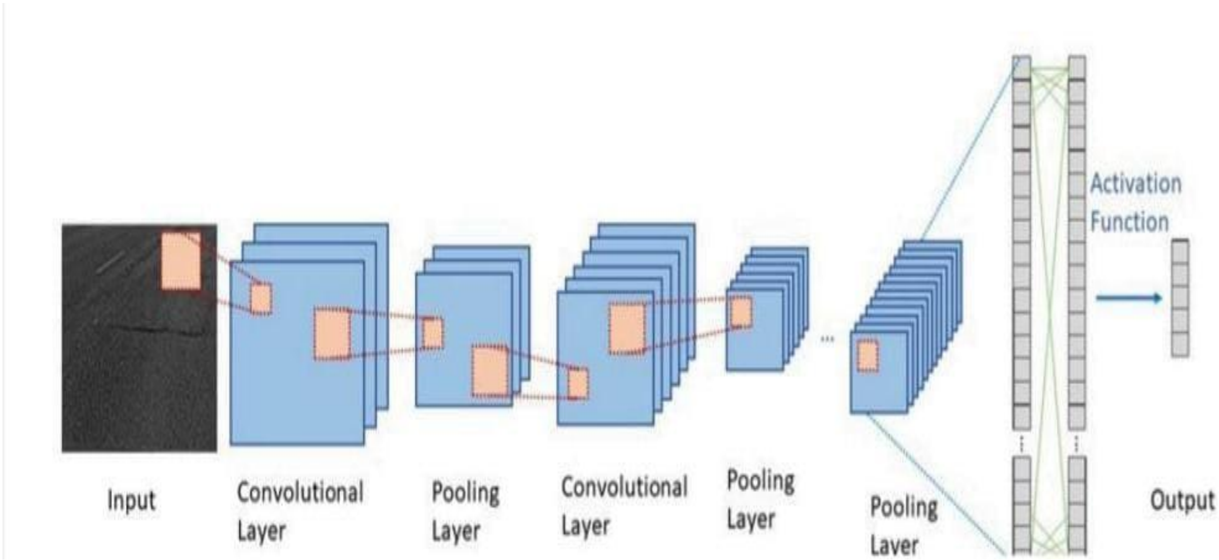

Figure 1: Proposed System

In the Feature Extraction stage, deep learning models automatically detect important patterns in the MRI scans. Unlike older machine learning methods that require manual selection of features, CNNs can learn from the image data itself. Models like InceptionV3 have shown great accuracy in doing this. The Tumor Classification module identifies whether a tumor is present and classifies it into one of several types, such as benign, malignant, or non-tumorous. The deep learning model is trained on a large number of labeled MRI images, allowing it to learn from many examples and improve its prediction accuracy. This greatly reduces the chances of a wrong diagnosis and supports doctors in making the right decisions.

The process starts with brain MRI images, which may be normal or show tumors. Preprocessing techniques like noise reduction and contrast enhancement are applied. A deep learning modelsuch as ResNet50, DenseNet, EfficientNet B1 , or InceptionV3—extracts features and classifies whether a tumor is present and identifies its type (e.g., glioma, meningioma, or pituitary). The final output indicates the tumor type or confirms a normal MRI, summarizing the complete automated detection and classification pipeline

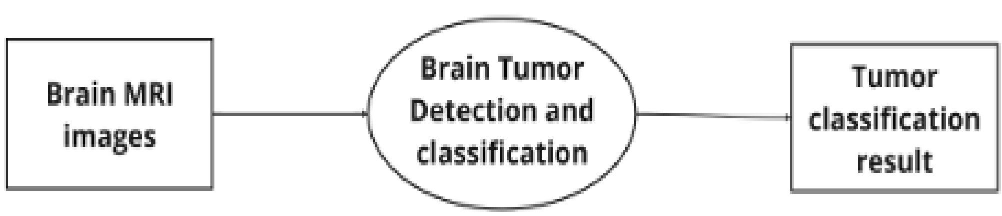

Figure 2: Output

3.2.Level 0:

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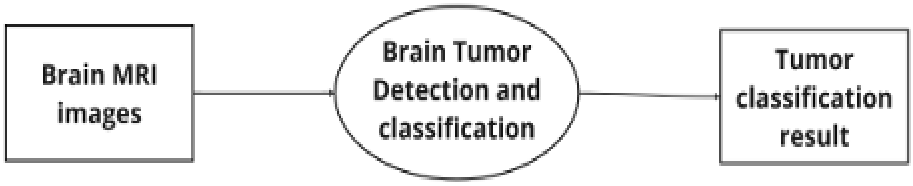

Figure 3: Level 0

3.3. Level 1:

- **Database**
  The storage location where MRI scan data is stored. This could be a hospital's medical records, a research repository, or a publicly available dataset.
- **MRI Dataset Collection**
  The process of gathering MRI images from the database or further processing.
- **Dataset Division**
  The collected dataset is split into different subsets to ensure effective model training and evaluation. Typically, it is divided into a training set and a testing set.
- **Training Set**
  The portion of the dataset used to train the machine learning model. The model learns patterns, features, and characteristics from these images to develop predictive capabilities.
- **Testing Set**
  The portion of the dataset used to evaluate the model's accuracy and generalization. It consists of images that the model has not seen before, helping to assess how well it performs on new data.

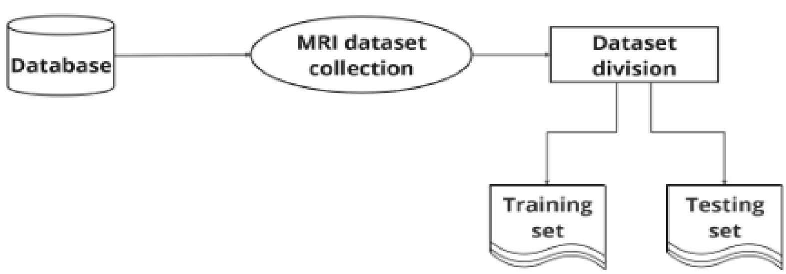

Figure 4: Testing Set

3.4. Level 2:

- **Training & Testing Sets**: Dataset is split into training (for model learning) and testing (for evaluation), both undergo preprocessing.
- **Preprocessing Stage**: Enhances raw MRI images for better model input. This stages may also involve preprocessing tasks like resizing, filtering, and augmentation to prepare the data for training cable.
- **Preprocessing Techniques:**
- **Normalization:** adjusts the pixel values of an MRI image so that they are within the same range, usually between 0 and 1. This helps the deep learning model process the images more easily and improves training speed and accuracy.
- **Noise Reduction:** removes unwanted random spots or distortions in the MRI scan. This makes the image clearer by focusing on important features like the tumor area and helps the model detect tumors more accurately.
- **Output:** Preprocessed images ready for model training and testing.

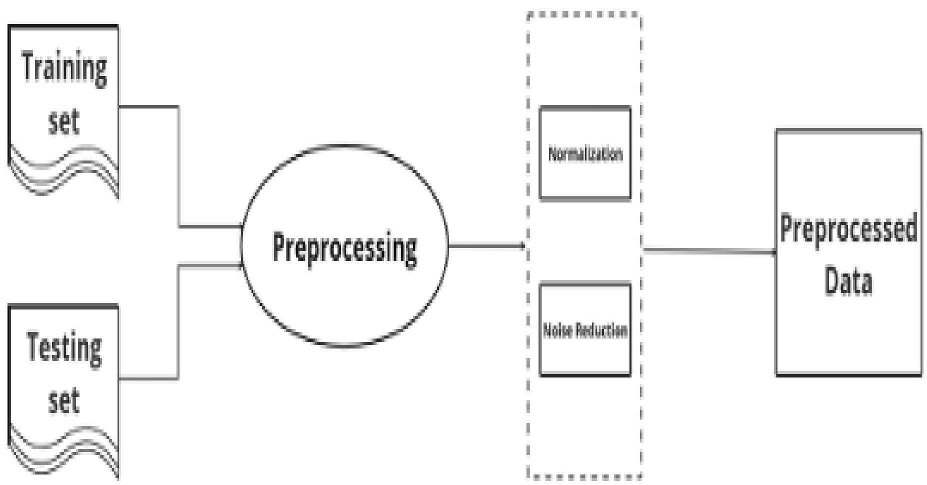

Figure 5: Level

3.5 Level 3

- **Training Phase**

  In this phase, MRI images are used to train four deep learning models: ResNet-50, DenseNet, Efficient Net B1, and Inception V3. Each of these models learns to recognize patterns and features related to different brain tumor types from the training data. The more the model sees, the better it becomes at understanding what different types of tumors look like.

- **Forward Propagation**

  Once the training begins, the images are passed through the layers of the model. This step is called forward propagation. The model analyzes the input image and makes an initial prediction, such as labeling a tumor as glioma, meningioma, pituitary tumor, or no tumor.

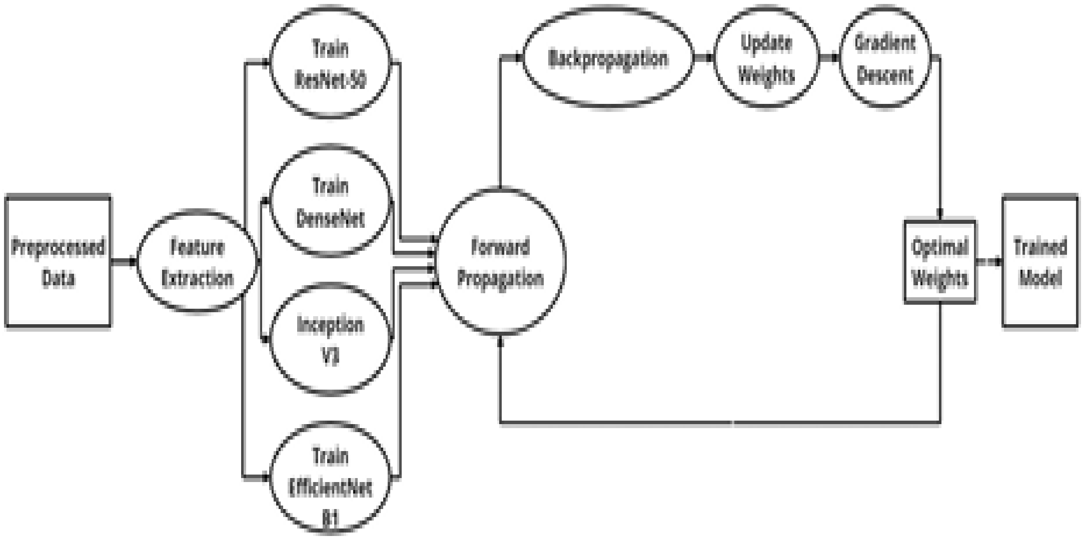

Figure 6: Level 3

- **Backpropagation**

  After the model makes a prediction, the system checks how far the result is from the correct answer. The error or loss is then sent backward through the model. This process is called backpropagation. It helps the model understand what it got wrong.

- **Update Weights**

  Using the feedback from backpropagation, the model updates the internal values called weights. These weights are what the model uses to make decisions. Adjusting them helps the model improve its predictions in the next training cycle.

- **Gradient Descent**

  To make these weight updates, an optimization method like Stochastic Gradient Descent (SGD) or Adam is used. These methods help the model find the best values for the weights so that the prediction error becomes smaller and smaller over time.

- **Optimal Weights**

  As training continues, the model keeps adjusting its weights. Once the prediction error is as low as possible and the model is performing well, the best (or optimal) weights are saved. These weights represent the learned knowledge of the model.

- **Trained Model**

  After many rounds of training, adjusting, and improving, the final trained model is ready. It can now accurately classify new MRI scans into different categories based on what it has learned during training.

3.6 Level 4

- **Test Data**

  MRI images used to test the model’s tumor classification accuracy

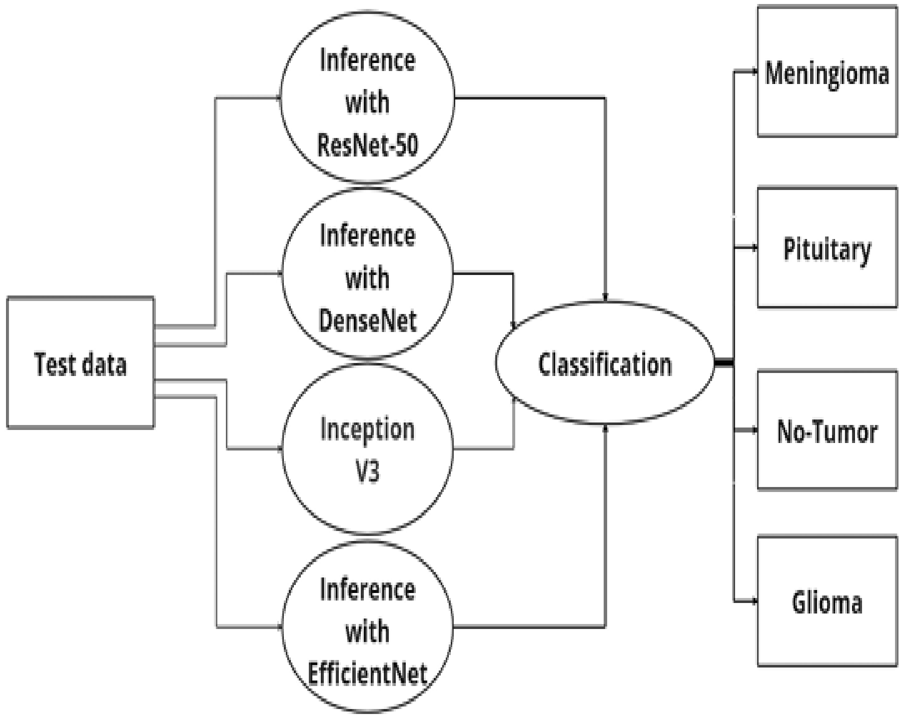

Figure 7: Level 4

- **Inference with ResNet-50**

  The model analyzes MRI scans to identify tumor presence by extracting important features.

- **Inference with DenseNet**

  DenseNet processes the data for improved feature extraction and tumor detection.

- **Inference with EfficientNet B1**

  EfficientNet classifies MRI images with optimized accuracy and computational efficiency.

- **Inference with Inception V3**

  InceptionV3 analyzes MRI images using its deep architecture to improve classification accuracy and feature extraction.

- **Classification**

  The system combines outputs from ResNet-50, DenseNet, and EfficientNet to classify the tumor type or detect no tumor.

- **Meningioma, Pituitary, No-Tumor, Glioma**

  The final classification labels the tumor as meningioma, pituitary, glioma, or no tumor

3.7 Level 5

- **Model Predictions and Ground Truth**

  Compares model predictions with actual labels to assess accuracy.

- **Calculate Accuracy**

  Measures the percentage of correct predictions to evaluate overall performance.

It is the ratio of (True Positives + True Negatives) to Total Predictions:

Accuracy = (TP + TN) / (TP + TN + FP + FN)

- **Calculate Precision**

  Determines how many predicted tumors are correct, minimizing false positives.

  It is the ratio of True Positives to Total Predicted Positives:

  Precision = TP / (TP + FP)

- **Calculate Recall**

  Measures how well the model identifies actual tumor cases, reducing false negatives.

  It is the ratio of True Positives to Total Actual Positives:

  Recall = TP / (TP + FN)

- **Calculate F1-Score**

  Balances precision and recall for a single performance metric, especially for imbalanced data.

  It is the ratio of twice the product of Precision and Recall to their sum:

  F1-Score = (2 * Precision * Recall) / (Precision + Recall)

- **Generate Confusion Matrix**

  Provides a detailed breakdown of correct and incorrect predictions for each tumor category.

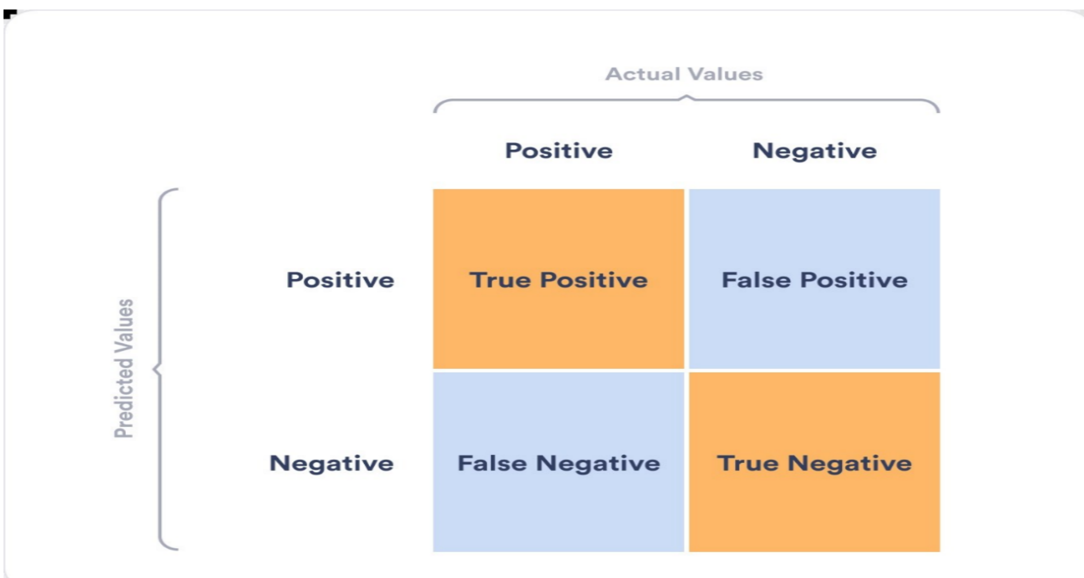

Figure 8: Level 5

- **Classification Report**

  Summarizes all metrics into a report to evaluate the model’s strengths and weaknesses.

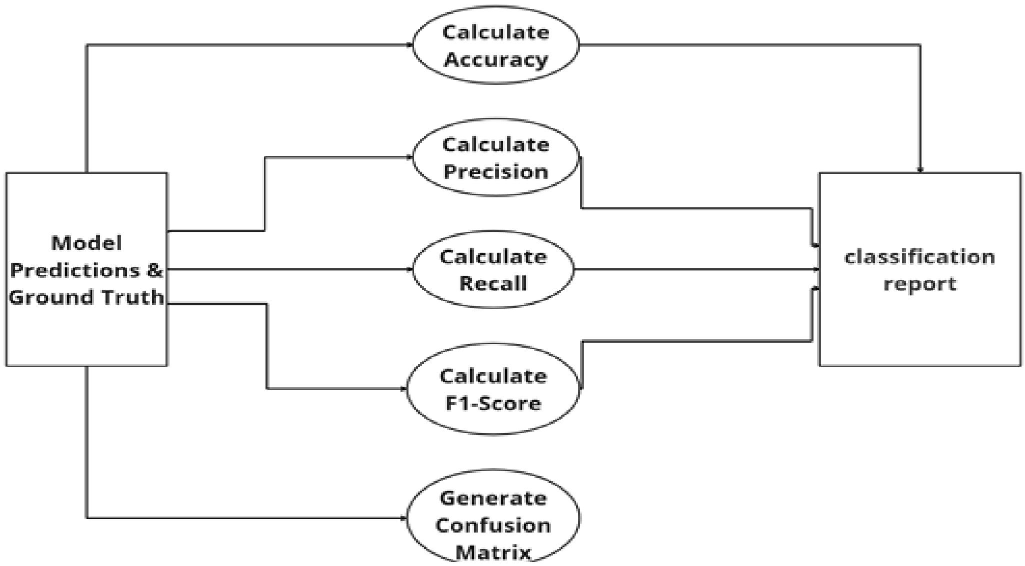

Figure 9: Classification Part

4. Requirement Specification

The development and implementation of the proposed brain tumor detection system using deep learning require a clear specification of hardware, software, and functional requirements to ensure an accurate, efficient, and user-friendly system.

Hardware Requirements

- **Processor:** Intel Core i7-10850H or above– to provide high processing power for handling complex computations, data processing, and blockchain transactions effi ciently.
- **GPU:** NVIDIA GeForce RTX 3060 or above– to support deep learning, image processing, and high-performance computing tasks required for forensic analysis.
- **RAM:** 8GBor above– to ensure smooth multitasking, real-time data processing, and seamless execution of blockchain transactions and AI models.

Software Requirements

- **Operating System:** Windows 10 or above– to ensure compatibility with develop ment tools, blockchain frameworks, and AI libraries.
- **Programming Language**: Python– used for backend development, blockchain integration, and AI-based forensic evidence processing.
- **Libraries:** TensorFlow, Keras, NumPy, OpenCV– essential for machine learn ing, deep learning, numerical computing, and image processing tasks in forensic investigations.

5. Result and discussion

	Existing system	EfficientNet B1	ResNet50	DenseNet	Inception V3
Accuracy	85	98	90	96	99
Precision	82	98	90	96	99
Recall	80	98	90	96	99
F1-score	81	98	90	96	99

Table 1: Result

The brain tumor detection and classification system integrates four deep learning models—InceptionV3, ResNet50, DenseNet, and EfficientNetB1. Among them, InceptionV3 delivered the highest accuracy and overall performance. All models successfully processed MRI images, extracted tumor features, and classified them into categories such as glioma, meningioma, or pituitary tumor. Preprocessing and augmentation techniques enhanced model generalization across datasets. The classification module effectively minimized false positives and distinguished normal from abnormal brain tissues. A clear visualization interface supported fast, reliable diagnosis. The system's modular design ensured smooth operation and accurate tumor detection from start to finish.

The table compares the performance of various models used for brain tumor classification based on MRI images. It evaluates four key metrics: accuracy, precision, recall, and F1-score. Among the models, Inception V3 outperforms all others with a consistent score of 99% across all metrics, indicating exceptional classification ability. Efficient Net B1 also shows strong performance with 98% in every category. DenseNet closely follows with 96%, while ResNet50 achieves 90% across the board. In contrast, the existing system lags behind, with accuracy at 85%, precision at 82%, recall at 80%, and F1-score at 81%. These results highlight the effectiveness of advanced deep learning models over traditional methods. The improvement in precision and recall, in particular, suggests that the newer models are better. at correctly identifying tumor cases while minimizing false positives and negatives, making them more reliable for medical diagnosis.

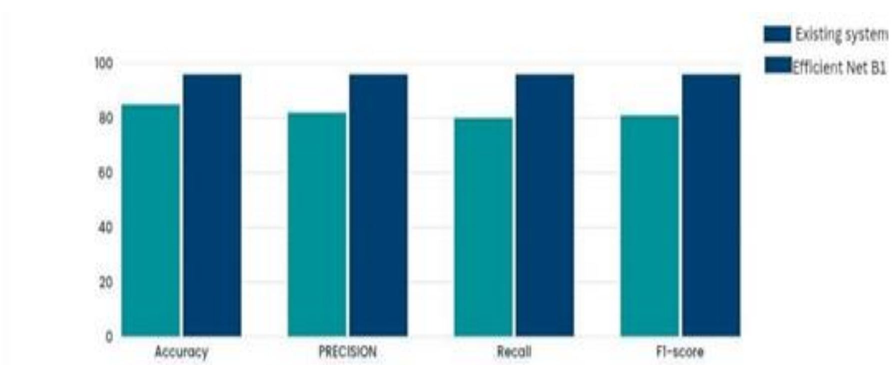

Figure 10: Performance Analysis

6.Conclusion

The proposed brain tumor detection system successfully uses deep learning models such as ResNet50, DenseNet, EfficientNetB1, and InceptionV3 to classify MRI scans into glioma, meningioma, pituitary tumor, and non-tumorous cases. With effective preprocessing steps including normalization, noise reduction, and data augmentation, the system ensures improved image clarity and better model generalization. The automated classification approach reduces the dependency on manual diagnosis, leading to quicker and more accurate results. By combining multiple CNN architectures and rigorous training, the system enhances diagnostic precision, minimizes errors, and supports early detection, contributing to better patient care and treatment planning. This project demonstrates how AI-powered tools can play a vital role in advancing healthcare and improving outcomes in medical imaging.

7. References

[1]. Geethanjali N,Mrs.V. Pushpalatha, Ramya C, Sandhiya L, SubhashriS"Brain TumorDetection and Classification Using Deep Learning" IEEE Winter Summit on SmartComputing and Network(WiSSCoN), 2023.

[2]. H.T. Zaw, N. Maneerat, K.Y. Win, "Brain Tumor Detection Based on Naïve Bayes Classification," International Journal of Biomedical Imaging and Analysis, 2019.

[3]. Ziqian Wang, Felix Dreyer, Friedemann Pulvermüller, Effrosyni Ntemou, Peter Vajkoczy, Lucius S. Fekonja, Thomas Picht, "Support Vector Machine-Based Aphasia Classification of Transcranial Magnetic Stimulation Language Mapping in Brain Tumor Patients," Journal of Forensic Sciences, 2021.

[4]. Krishan Kumar, Kiran Jyoti, "Explainable AI in Brain Tumor Diagnosis: A Critical Review of ML and DL Techniques," Journal of Cloud Computing, 2024.

[5]. Javeria Amina, Muhammad Sharifa, Mussarat Yasna, Steven Lawrence Fernandes, "A Distinctive Approach in Brain Tumor Detection and Classification Using MRI," International Journal of Digital Evidence Management, 2020.

[6]. R. Anitha, D. Siva Sundhara Raja, "Development of Computer-Aided Approach for Brain Tumor Detection Using Random Forest Classifier," IEEE International Conference on Intelligent Systems and Neural Networks, 2018.

[7]. Gopal S. Tandel, Antonella Balestrieri, Tanay Jujaray, Narender N. Khanna, Luca Saba, Jasjit S. Suri, "Multiclass Magnetic Resonance Imaging Brain Tumor Classification Using Artificial Intelligence Paradigm," IEEE Access, 2020.

[8]. M. Soltaninejad, L. Zhang, T. Lambrou, G. Yang, N. Allinson, X. Ye, "MRI Brain Tumor Segmentation Using Random Forests," IEEE International Conference on Computer Vision and Pattern Recognition (CVPR), 2019.