MRI-based Detection, Classification and Grade Prediction of Brain Tumor using Transfer Learning and Support Vector Machines

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Abstract

Brain Tumors detection, classification and grade prediction according to WHO standards using MRI images remain a highly challenging task. Conventional machine learning and deep learnings models often fails to perform well when the dataset is very small, inaccurate and imbalanced, which is very common in medical imaging. To overcome these limitations, the proposed approach introduces an MRI- based framework for brain tumor detection, classification and grade prediction using transferring learning and support vector machines. MRI is the most widely used imaging modality for brain tumor detection due to its excellent soft-tissue contrast and non-invasive nature. This experiment focuses on the advancement of an intelligent framework for detection, classification and grade prediction of brain tumor using transfer learning techniques. Initially, a basic convolutional-based neural networks is used to detect the MRI images into tumor-positive and tumor-negative groups. Once the presence of tumor is confirmed, a classification technique is applied to find the types of tumors. In the grade prediction stage, machine learning classifiers such as Support Vector Machine are employed to determine tumor aggressiveness. The proposed approach aim is to improve the diagnostic accuracy of 95% or above, support the clinical decision-making and reduce the human intervention. The proposed framework is the combination of detection, classification and grade prediction. Tumor detection using a basic CNNs model, classification using DenseNet121 and tumor grade prediction using ML classifier. The experimental analysis provides the reliability, stable performance, making the system suitable for the real-world application.

Keywords: Brain tumor, CNN, DenseNet 121, SVM, KNN, MRI

Introduction

Brain tumors arise from abnormal and uncontrolled growth of cells within the brain or its surrounding tissues. Based on biological nature, tumors are generally grouped into two categories of tumor that are benign (malignant) and non-malignant. Malignant causes aggressive behaviour and rapid progression. According to medical studies, early-stage tumor

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detection significantly increases survival rates and improves treatment outcomes. Therefore, accurate diagnosis at an early stage can saves many lives, and is critically important in neuro-oncology. MRI provides clear visualization of soft tissue structures without exposing patients to ionizing radiation, making it a vital tool in brain tumor diagnosis. Although imaging technologies have advanced significantly analysing MRI scans remains a challenging work. Radiologists must analyse a large number of slices for each patient, which increases workload and the risk of diagnostic errors.

To assist radiologists, automated computer-aided diagnosis systems are increasingly being used as supportive tools for medical image processing. Convolutional neural networks have emerged powerful tool in medical image analysis, as they automatically learn discriminative features directly from raw image data, eliminating the need for traditional handcrafted feature extraction methods [1]. A survey reports given by WHO says that around 29% patients are affected by Malignant tumors and remaining 71% of patients having brain tumors are affected by benign tumors and most of them are Americans [2].

Classification of brain tumor depends on its originates and severity or currently where it is present. Classification based on its location is either primary or secondary, that if it originates from brain or remains inside it then it is primary. Otherwise, if it originates from some other parts of body and travels towards the then it is secondary. For example, a patient undergoing an MR imaging scan after experiencing frequent headaches. Scan reveals the small abnormal region of tissues/cell in brain that could be the Glioma tumor. Rather than waiting for manual scan or analysis, a hybrid system studies the images, learn important patterns and feature using the machine learning classier, and very quickly determine the grade of tumor i.e., low grade (LGG) or high grade (HGG). The early and accurate prediction helps the doctors to decide the right treatment at absolute time can the patient's life potentially [3].

Related Work

The earliest study on brain tumor classification, the study proposed Pashaei et al. relied on a custom CNN (5 layers) combined with Extreme learning machine. While this model achieved the accuracy of 81% with the Figshare dataset and were work on only 3 classes. Feature extraction is carried out using CNN Extreme learning machine (ELM) for classification. It was fully automatic with no ROI. The model was the poor discrimation for meningioma class. Afsar et al. works on CapsNet with the same dataset which capture the spatial relationship between surrounding tissues and the tumor. The method uses in it were spatial relationship learning using capsules with the slight improvement over CNN in term of accuracy and computationally hard. Deepak & Ameer, major improvement was introduce using GoogleNet (Transfer learning) with the accuracy of 98%, high AUC, precision, recall, Specificity. The method used were Patient-level 5-fold cross validation with deep features SVM \KNN. But the dataset classes were imbalance and improper, not tested on glioma grading, depends on transfer model [2].

CNN Model for LGG/HGG Glioma, using method CNN for Glioma grading with only binary classes (LGG/HGG). Slice wise CNN training with reasonable accuracy but only with slice level not volume level, no patient CV [3]. EfficientNet Transfer learning (Scientific Reports) study fine- tuned transfer learning, EfficientNet B0-B4 augmentation with the 3 types of tumor classes. This were achieved the highest accuracy with Figshare 3064 T1-CE MRI images. While the complete works depends on single dataset, no noisy MRI evaluation. Subsequently, Hafeez et al. designed a lightweight CNN compared with ResNet18, SqueezeNet and AlexNet tested on BraTS17-19 and private dataset (real hospital dataset). Achieved the greater accuracy but doing only the grade prediction. It works on grade classification; cross- dataset validation with limited depth architecture [5].

Pande & Chaki presented feature fusion from ResNet101 combined with DenseNet121, dimensionality reduction techniques were employed from PCA and for classified using random forest. The work tested on 5 datasets (clean +noisy) with 4 classes of tumor, high training time and complex pipeline with accuracy of 98.1%. [1] Next, Jebin et al. separated the brain tumor region and brain texture with dataset of figshare, Br35H, SARTAJ. The methods were texture pattern combined with complementary U-Net and CNNs, complex preprocessing (IMF, FCM, histogram equation) [9]. Ismael & Abdel-Qadar, were work on same dataset with the train -test split of 70\30. It introduces texture-based features using Gabor-filters and DWT with ML classifiers. The model increasing the possibility of model overfitting and information leakage [11]. Cheng et al., based on manual tumor border segmentation which is followed by handcraft SVM and feature exaction for classification. While this model achieved an accuracy which is reasonable on the Figshare datasheet. They were depended heavily on ROI extraction which were not fully automatic and also the limitation of clinical applicability [12].

Several works combined Ensemble Deep learning, Machine learning, EfficientNet, ELM and VGG19 for feature fusion, optimization, ELM/RF with public dataset. The model achieved highest accuracy, trained on clean MRI only, ensemble reduces overfitting. Very few were works on LGG vs HGG grading. and handles noisy clinical MRI images. The very few models use the deep feature fusion merges with ML classifier. Most high-accuracy paper do detection, classification only, but few do grade prediction. Most paper work uses figshare dataset works focus on tumor type not grade. No comparison between SVM vs CNN SoftMax, lack of patient-level cross validation. In Table 1, comparison of related study with the proposed work.

Table 1 Comparison of different tumor detection, classification and grade prediction

Authors	Year	Task Type	Dataset Used	Approach / Model Used
Ismael & Abdel-Qader [12]	2018	Classification	Private MRI dataset	Statistical features + Back-Propagation Neural Network
Deepak & Ameer [2]	2019	Classification	Figshare (3064 images)	Modified GoogLeNet + SVM/KNN (Transfer Learning)
CNN-based Glioma Grading [8,21]	2020	Grade Prediction	BraTS 2017–2019	CNN end-to-end model

Hafeez et al. [6]	2023	Grade Prediction	BraTS + Hospital MRI	Lightweight CNN (compared with ResNet, AlexNet)
EfficientNet Transfer Learning [5]	2023	Classification	Figshare	EfficientNet-B0 to B4 (Transfer Learning)
Ensemble CNN + ML [13]	2022	Detection & Classification	Public MRI datasets	CNN + Feature Fusion + RF/ELM
Jebin et al. [9]	2025	Detection & Classification	Figshare, Br35H, SARTAJ	Complementary Kernel U-Net + CNN
Pande & Chaki (INDEMNIFIER) [1]	2025	Detection & Classification	Clean & Noisy MRI datasets	ResNet + DenseNet feature fusion + PCA + RF
Proposed work	Present	Detection + Classification + Grade Prediction	Kaggle dataset	CNNs+Densenet121+ SVM

Methodology

This research purposes a combination of three approach for brain tumor detection, classification and grade prediction using MRI images. The block diagram of proposed approach is demonstrated in Fig. 1.

System overview

The proposed framework performs three main analytical tasks in brain MRI processing:

- Tumor Detection – Determine whether the abnormal tissues present or not.
- Tumor Classification- classified the tumor types into multiple classes using MRI slice.
- Tumor grade feature extraction(prediction) – Assigns tumor severity into binary grade classes.

The well-designed architecture integrates image processing, deep learning (CNN), radiomic feature engineering to ensure accurate and reliable analysis.

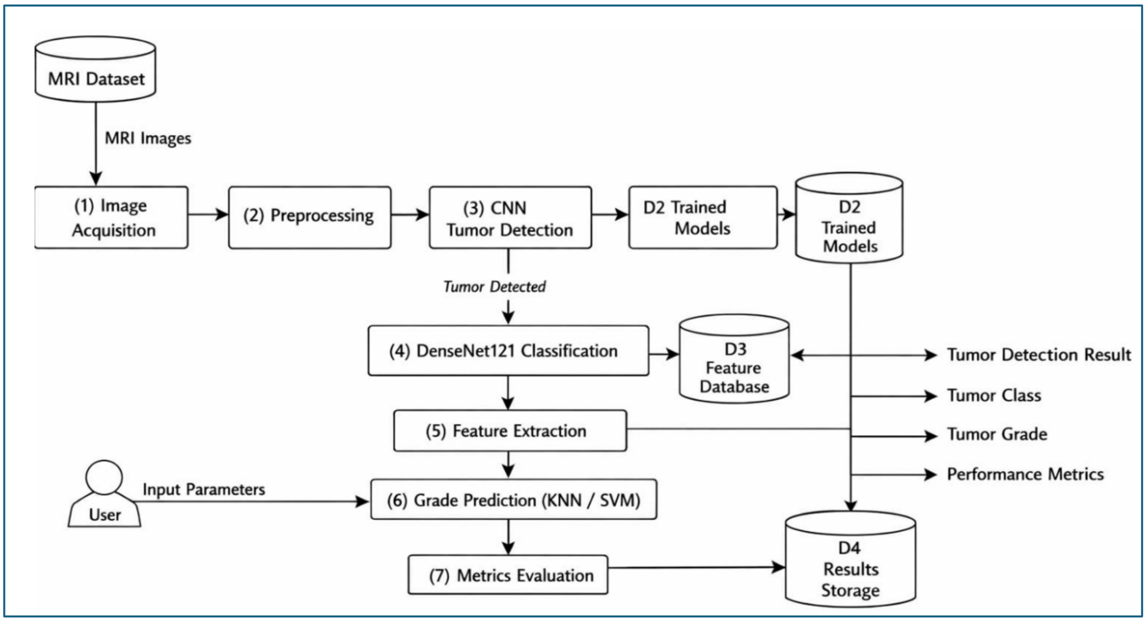

Fig. 1 Block diagram of Proposed Work

Figure 1 illustrates a step-by-step pipeline for brain tumor analysis using MRI data. It begins with collecting MRI images, which are then cleaned and prepared through preprocessing to improve quality. These processed images are passed into a CNN model that detects the presence of a tumor, and the trained models store learned patterns for accuracy. Once a tumor is identified, a DenseNet121 model classifies it into specific categories, after which important features are extracted from the images. These features, along with user-provided inputs, are used by machine learning models like KNN or SVM to predict the tumor grade. Finally, the system evaluates its performance and stores the results, including tumor detection, classification, grading, and overall accuracy metrics, in a structured results database. The system achieved 94.73% detection accuracy of tumors, 95% for classifying tumor types and 82.43% in grade prediction, demonstrate its effectiveness for automated MRI-based diagnostic assistance.

Implementation

Image acquisition: MRI images were acquired from structured datasets containing multiple classes of brain tumors available on Kaggle [24]. The brain tumor datasets are commonly classified into the following categories:

- Glioma
- Meningioma
- Pituitary
- Normal tissue (NO tumor)

For tumor grade prediction according to WHO classification, a volumetric dataset available on Kaggle [25] was used. The MRI volumes were stored in .h5 format were processed slice by slice. The processing steps included:

- Grouping slices belonging to the same patient volume.
- Reading multi-modal MRI channels (T1, T1CE, T2, Flair)
- Extracting tumor region masks.
- Uses only two classes Low Grade Glioma (LGG) and High-Grade Glioma (HGG).

The processing pipeline consisted of the following steps:

Resizing → Normalization →Data augmentation

- Resizing - All images were resized to a fixed resolution to standardize spatial dimensions and reduce computational cost.
- Normalization - After resizing, pixel intensity values were scaled to range of 0 to 1 using the following formula:

$$X(norms) = \frac{X}{255} \quad (1)$$

As shown in (1), normalization improves gradient stability and accelerates model convergence during training.

- Data Augmentation – It was applied to reduce overfitting and increases sample diversity. The augmentation techniques included:

Rotation; Flipping; Zooming

The transformations artificially expand the dataset and improve the model's generalization capability.

CNN and Advanced Deep Learning Architecture

CNNs are highly effective for image classification tasks because convolutional layers learn local spatial patterns, pooling layers reduces dimensionality and fully connected layers perform classification. As shown in Table 2, CNNs architecture consists of the following components:

- Convolutional layers
- ReLU activation function
- Pooling layers
- Flatten layers
- Dense layer
- SoftMax output layer

Table 2 CNNs Architecture

Layer	Function
Input Layer	Accepts 224×224 RGB image

Conv2D (32 filters)	Spatial feature extraction
MaxPooling	Dimensionality reduction
Conv2D (64 filters)	Deeper feature learning
MaxPooling	Further compression
Flatten	Converts feature maps to vector
Dense (128)	Nonlinear representation learning
Dropout (0.5)	Overfitting prevention
Dense (SoftMax – 4 classes)	Final classification

Training configuration – The model is trained using a croos-entropy loss function optimized with the Adam optimizer.

- Epochs – 40
- Batch size – 32

A custom sequential CNN model was implemented using TensorFlow/Keras.

An advanced deep learning architecture, DenseNet121 is used for improved classification performance. DenseNet introduces dense connectivity, where each layer receives input from all preceding layers. This structure ensures strong gradient flow, encourages feature reuse, and minimizes information loss as shown in (2).

For an input image X, b is bias term, Y (i, j) output feature map and W is kernel filter, the convolution output at location (i, j) is defined as:

$$Y(i,j) = \sum_{n} X(i+n).w(n) + b \quad (2)$$

MRI tumor features may include:

- Micro-textures patterns
- Shape irregularities
- Region Contrast variations
- DenseNet preserves both low-level details and high-level abstraction.

DenseNet -121 consists of 121 layers, providing an optimal balance between depth and computational efficiency. It has demonstrated strong performance in medical imaging tasks due to its advanced feature extraction capability, effective transfer learning framework and high tumor identification accuracy.

Tumor Grade features extraction module

Tumor grade prediction estimates the severity of the disease at patient level. The proposed method utilizes statistical feature extraction based on volumetric features of the tumor.

Tumor grade measurements include the following features:

- Tumor Core volume
- Edema volume
- Enhancing region
- Intensity statistics

Radiomics-based features quantify tumor aggressiveness and the extent of its spread in oncological modelling. These features improve interpretability by analysing the segmented tumor region and volume statistics. The extracted statistical features are used to make interpretable grading decisions. Well-established classifiers such as SVM and RF (Random Forest) are employed mainly for binary tumor grade prediction. These classifiers are effective for structured feature data provide robustness along with improved interpretability in medical decision-making.

Performance evaluation

The evaluation metrics were computed from the confusion matrix to measure the correctness, sensitivity, and balance between false positives and false negatives, ensuring a robust performance analysis of the proposed framework. The performance of proposed model was evaluated using standard classification metrics:

(a) Precision (b) Recall (c) Accuracy (d) F1- score

True Positive (Tp); True Negative (Tn); False Positive (Fp); False Negative (Fn)

a) Precision – Calculates the percentage of predicted positive cases that are correctly identified, reflecting the trustworthiness of the model's positive outputs.

$$Precision = \frac{Tp}{Tp + Fp} \qquad (3)$$

As shown in (3), precision is defined as the ratio of true positive predictions to the total predicted positive cases, measuring the accuracy of the model's positive predictions.

b) Recall – Determines the proportion of true positive cases that are accurately detected by the model.

$$Recall = \frac{Tp}{Tp + Fn} \qquad (4)$$

As shown in (4), recall is defined as the ratio of true positive predictions to the total actual positive cases, measuring the model's ability to correctly identify all positive instances.

c) Accuracy – Represents the overall percentage correctly classified instances out of all prediction.

$$Accuracy = \frac{Tp + Tn}{Tp + Tn + Fp + Fn} \qquad (5)$$

As shown in (5), accuracy is defined a ratio of correctly predicted instances (true positives and true negatives) to the total number of predictions, reflecting the overall performance of the model.

d) F1-score – Combines precision and recall into a single metric, providing a balanced evaluation of the model's performance.

$$F1 - score = \frac{2 * Precision * Recall}{Precision + Recall} \quad (6)$$

As shown in (6), the F1-score is defined as the harmonic mean of precision and recall, providing a balanced measure of the model's performance.

For real world application

Streamlit was used to develop a simple and interactive interface for the brain MRI image classification system, enabling deep neural network model to be applied in a practical, real-world setting rather than remaining limited to research experiments, as shown in Fig 2.

It transforms the CNN-based brain MRI model into an easy-to-use web application. The platform allows users to upload MRI images and instantly receive tumor type or grade predictions without requiring technical knowledge. This makes the system practical for real-world clinical use by doctors and radiologists, help to save time and support faster clinical decision-making.

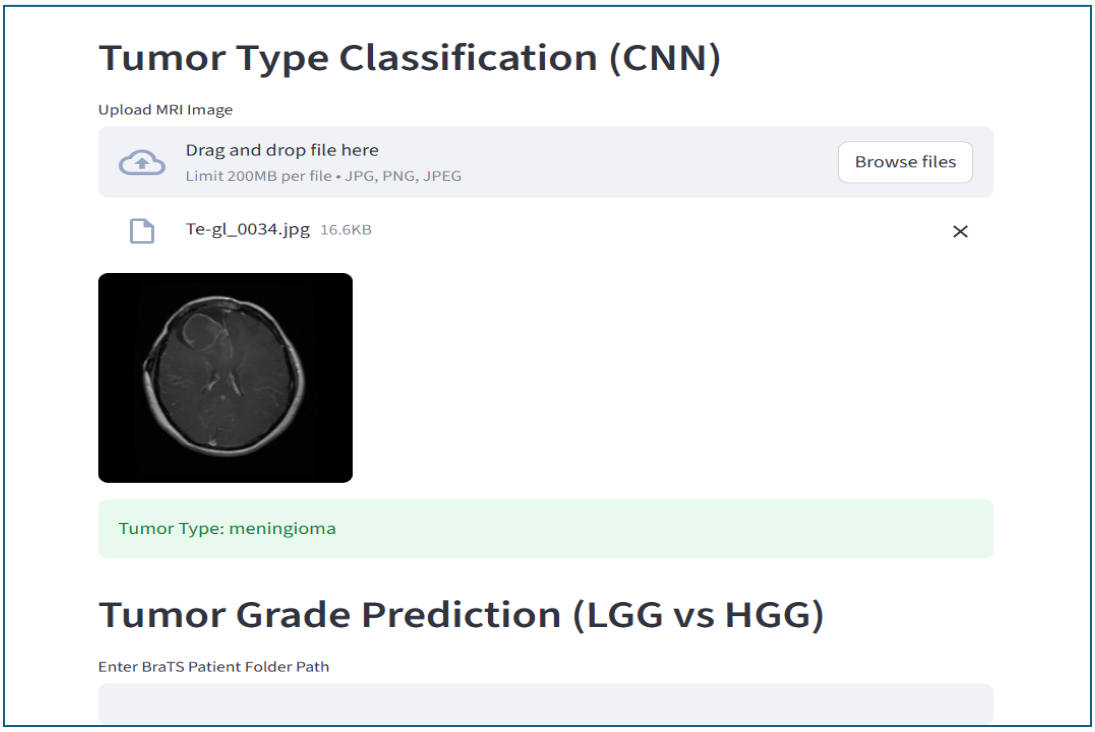

Fig. 2 – Web-based interface

Result and Discussion

This study evaluates different learning approaches to determine the accuracy rate, precision, recall, F1- score and other performance parameters. The evaluation focused on mainly three tasks: Tumor detection, Tumor-type classification, and Tumor grade prediction. Multiple deep learning and various machine learning techniques were assessed to determine the most effective model configuration under identical experimental conditions. In our experiment, we used a hp laptop with 8Gb RAM, 477 GB SSD, processor of 12th gen intel® core and system type are 64-bit operating system, x64-based processor. We use Anaconda 3 as the virtual environment with jupyter notebook for python employing TensorFlow\ Keras deep learning components, Scikit-learn for conventional machine learning algorithms and importing some libraries like sklearn-meterics for classification-report, confusion-matrix. The system was executed on a standard personal computing setup to validate that the proposed methodology remains computationally feasible without specialized hardware.

Datasets-

For this study, the proposed classification model was trained and evaluated using two publicly accessible brain MRI datasets from Kaggle in Fig 3. The Brain Tumor MRI Dataset typically includes around 7023 images across four classes (glioma, meningioma, pituitary, no tumor) [24]. IN Fig 4, Brain Tumor MRI Dataset typically includes around 369 patient images across T1, FLAIR, T1CE, T2 and Ground Truth [25].

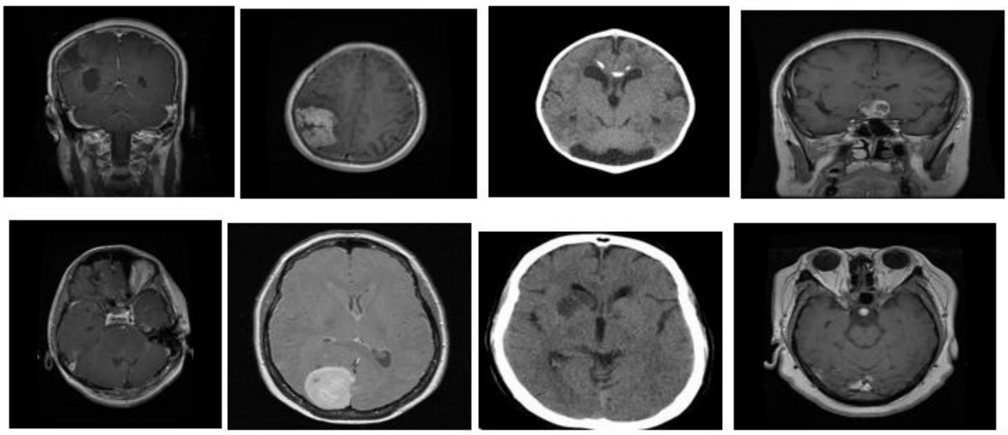

Fig. 3 dataset 1

In Fig. 3, The 1st row shows the training images and the 2nd shows the testing images; (a) Glioma tumor, (b) Meningioma tumor, (c) no-tumor, (d) Pituitary tumor.

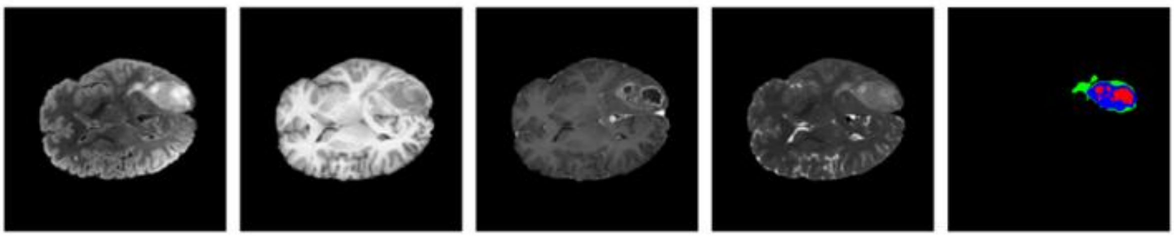

Fig. 4 dataset 2

In Fig.4 some various MRI modalities employed for grading prediction are T1, FLAIR, T1CE, T2 and Ground Truth.

Table 2 Overview of datasets used for brain tumor analysis tasks

Dataset	Task	Train	Test	Total
Brain Tumor MRI dataset	Detection\ Classification	5712 images	1311 images	7023 images
BraTS2020 Training Data	Grade Predication	125 cases	169 cases	294 images

Table2 summarizes two datasets utilized in the study along with their respective tasks and data distribution. The Brain Tumor MRI dataset is used for detection and classification, containing 5712 training images and 1311 testing images, making a total of 7023 images. The BraTS2020 Training Data is used for grade prediction, consisting of 125 training cases and 169 testing cases, with a total of 294 cases. This comparison highlights the difference in data type (images vs. cases) and the specific purpose each dataset serves in the analysis pipeline.

Detection and Classification Performance Analysis - The CNN trained using MRI images demonstrated strong capability in distinguishing tumor and no-tumor cases. Feature representations extracted from DenseNet 121 significantly improved the classifier on raw image features. For multi-class categorization of tumor types, deep features generated by DenseNet 121 were passed to a machine learning classifier. Among tested models, the hybrid CNN-feature + advanced deep learning features produced the most consistent performance. The individual accuracy for detection using basic CNN was 94.73% and for classification using DesneNet121 was 95%. In Table 3, the assessment of tumor detection and classification results having the individual tumor types with precision, recall and F1-score.

Table 3 Assessment of detection and classification of Tumor types

Tumor Types	Precision	Recall	F1-score
Glioma	0.9	0.99	0.94
Meningioma	0.98	0.83	0.9
Notumor	0.97	0.99	0.98
Pituitary	0.96	0.98	0.97

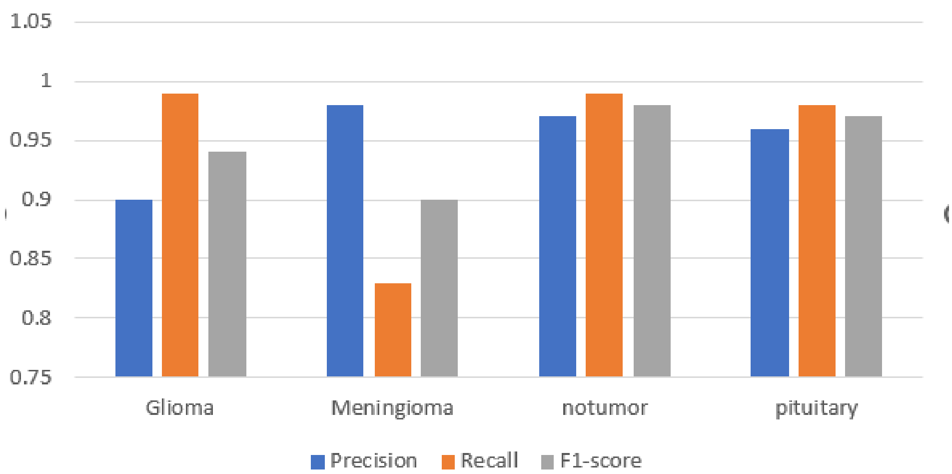

Fig. 5 Class-wise performance analysis of Tumor types.

Fig. 5 illustrates the precision, recall, and F1-score for different tumor classes: Glioma, Meningioma, No Tumor, and Pituitary.

Tumor Grade prediction evaluation – Tumor grading is inherently more complex due to subtle morphological differences between the classes. The machine learning classifier trained on extracted deep features achieved reliable predictive performance, as shown in Table 4. The accuracy for grade prediction according to WHO is 82.43%

Table 4 Evaluation for tumor grade prediction.

Class	Precision	Recall	F1-score
Grade 0	0.91	0.45	0.61
Grade 1	0.81	0.98	0.89

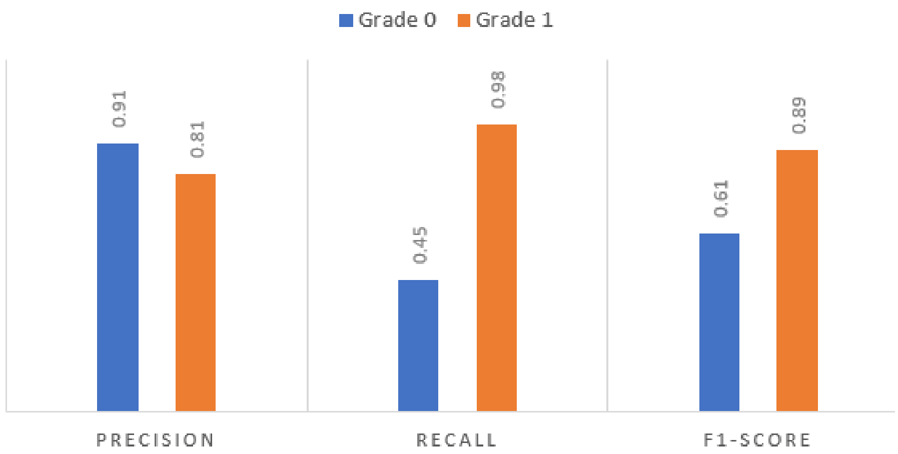

Fig. 6 Performance comparison of Grade0 and Grade1 tumor

Fig. 6 presents the precision, recall, and F1-score for Grade 0 and Grade 1 tumor prediction. Grade 1 shows significantly higher recall and F1-score compared to Grade 0.

The experimental outcomes in Table 5 suggest that integrating all the 3 works in one frame make my model very unique. Deep feature extraction with traditional classifiers yields superior generalization compared to standalone approach. DenseNet 121 effectively captures spatial and textural characteristics of MRI scans.

Table 5 Performance metrics of proposed models

	Model	Accuracy	Precision	Recall	F1-score
Detection	CNN	94.73	94	95.54	94.76
Classification	DenseNet121	95	95	96	95
Grade Predication	SVM	82.43	82	84	80

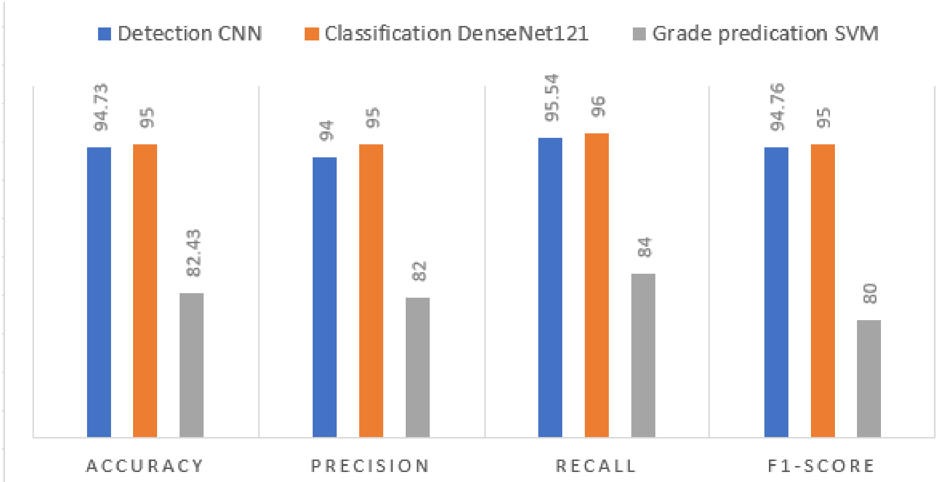

Fig. 7 Model performance comparision

Fig. 7 compares the performance of CNN (detection), DenseNet121 (classification), and SVM (grade prediction) using accuracy, precision, recall, and F1-score. DenseNet121 shows the highest overall performance, while SVM achieves comparatively lower scores.

Key observations include –

- Transfer learning reduced training time and improved the stability.
- High recall values indicate clinical screening usefulness.
- Grade prediction remains the most challenging tasks.
- Hybrid modelling enhanced the classification robustness.

Overall, the system demonstrates potential as a supportive diagnostic tool. The observed performance variation highlights the importance of task-specific model selection within multi-stage MRI system.

Limitation and Future work

Although the proposed framework demonstrates encouraging performance in detection, classification and grading brain tumors detected from MRI data, certain limitations should be acknowledged. The models were trained and evaluated on a limited dataset that may not reflect the full diversity of clinical imaging conditions. Classification training time was more-longer because of the unavailability of GPU. In addition, cross-institution or clinical validation was not performed. The prototype deployment was not tested in real hospital setting; it is only tested on the Kaggle dataset. Future research may explore architectures or feature- attention mechanisms to enhance grading sensitivity. Incorporating the larger and more heterogenous datasets would strengthen generalization capability and reduce bias. Additionally, integrating interpretability tools would improve transparency and user confidence. Extending this prototype into a clinical integrated system evaluated by healthcare professionals would represent an important step towards real-world implementation.

Conclusions

The proposed work was designed to address three key diagnostic approaches within a single system: detection of tumor presence, classification of tumor types and prediction of tumor grade. The study presented a multi stage compactional framework for automated brain tumor analysis. A CNNs was employed for tumor detection and achieved a high accuracy, indicating its effectiveness in identifying abnormal patterns within MRI images. For tumor classification, a pretrained deep learning, DenseNet 121, was adopted to extract features from multiple tumor categories. Although the grade prediction stages implemented using Support vector machine (SVM). Although the grading task proved more challenging than screening and classification, the model achieved reliable performance. In conclusion, the developed framework adds to the expanding body of research in intelligent medical imaging support systems. While not intended to replace the clinical judgement, the system demonstrates how algorithmic analysis can enhance efficiency, preliminary and consistency screening capability.

Declarations

Conflicts of interest: The authors declare that they have no conflicts of interest.

Funding: This research received no external funding.

Informed Consent: Not applicable.

Research involving humans or animals: Not applicable.

Data Availability: The datasets used in this study are publicly available and were obtained from the Kaggle platform. Specifically, the BraTS2020 Training Data (Awsaf49, 2020) and the Brain Tumor MRI Dataset (Masoud Nickparvar, 2024) were utilized for model development and evaluation. Both datasets can be freely accessed online through their respective Kaggle repository links.

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