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ВЫПУСКНАЯ КВАЛИФИКАЦИОННАЯ РАБОТА

ARTIFICIAL INTELLIGENCE FOR MEDICAL DIAGNOSIS USING MACHINE LEARNING FOR BRAIN TUMOR MRI CLASSIFICATION

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Artificial Intelligence for Medical Diagnosis Using Machin Learning for Brain Tumor MRI Classification

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I Abstract

The integration of Artificial Intelligence (AI) into the domain of medical diagnostics has ushered in a new era of precision, speed, and reliability, particularly in the analysis of medical imaging. Among the most promising applications is the use of Machine Learning (ML) techniques for the classification and diagnosis of brain tumors from Magnetic Resonance Imaging (MRI) scans. Brain tumors, whether malignant or benign, pose significant health threats and require early, accurate detection to improve prognosis and treatment outcomes. Traditional methods for diagnosing brain tumors are often time-consuming, subject to inter-observer variability, and reliant on the expertise of radiologists. This thesis explores the use of AI-driven machine learning models to automate and enhance the diagnostic process by classifying brain tumor types from MRI images.

This research presents a comprehensive study on the implementation of various machine learning algorithms—including Convolutional Neural Networks (CNNs), Support Vector Machines (SVM), and ensemble models—for the classification of different types of brain tumors, such as gliomas, meningiomas, and pituitary tumors. The dataset employed comprises a substantial number of pre-processed and labeled MRI images sourced from publicly available medical imaging repositories. The study begins with a detailed examination of MRI imaging modalities, the clinical characteristics of common brain tumors, and the importance of accurate classification.

A robust preprocessing pipeline was designed to handle data augmentation, normalization, and artifact removal, which are critical for enhancing image quality and improving model generalization. Feature extraction techniques, both handcrafted and automated via deep learning, were analyzed to assess their effectiveness in capturing the unique spatial and textural patterns of different tumor types. Subsequently, multiple supervised learning algorithms were trained and tested using cross-validation to compare their accuracy, precision, recall, F1-score, and area under the receiver operating characteristic (ROC) curve.

CNN-based architectures, particularly those leveraging transfer learning (e.g., ResNet, VGGNet, and EfficientNet), demonstrated superior performance compared to traditional classifiers, achieving classification accuracies exceeding 90% in test scenarios. In addition, model interpretability techniques such as Grad-CAM and SHAP were applied to visualize and explain the decision-making process of the neural networks, addressing one of the key challenges in deploying AI systems in clinical environments: trust and transparency.

Keywords:

Artificial Intelligence (AI), Machine Learning (ML), Brain Tumor, Medical Diagnostics, MRI (Magnetic Resonance Imaging), Brain Tumor Classification, Convolutional Neural Networks (CNN), Support Vector Machines (SVM), Ensemble Models, Glioma, Meningioma, Pituitary Tumor, Medical Imaging, Deep Learning, Transfer Learning, ResNet, VGGNet, EfficientNet, Image Preprocessing, Data Augmentation, Normalization, Artifact Removal, Feature Extraction, Supervised Learning, Cross-Validation, Accuracy, Precision, Recall, F1-Score, ROC Curve, Grad-CAM, SHAP, Model Interpretability, Diagnostic Automation, Radiology, Clinical AI, Trust and Transparency in AI.

Contents

Abbreviations

ML	Machin Learning
AI	Artificial Intelligence
CNN	Convolutional Neural Network
CSV	Comma Separated Values
DL	Deep Learning
GC	Garmin Connect
GPS	Global Positioning System
MRI	Magnetic Resonance Imaging
LSTM	Long-Short Term Memory
CNS	Central Nervous System
MEG	Magnetoencephalography
CT	Computed Tomography
PET	Positron Emission Tomography
CAD	Computer-Aided Diagnosis
MSCNN	Multi-Scale Convolutional Neural Network
TCX	Training Center XML
FSNLM	Fuzzy Similarity-based Non-Local Means
BTC	Brain Tumor Classification
NN	Neural Network
BT	Brain Tumor
WHO	World Health Organization
VGG	Visual Geometry Group
CBOSS	Contractable Bag of Symbolic Fourier Approximation Symbols
CTSF	Composable Time Series Forest
CE	Column Ensemble
DT	Decision Tree
G-NB	Gaussian Naïve Bayes
GB	Gradient Boosting

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Introduction

1.1 Problem description

Brain tumors are among the most life-threatening and complex medical conditions, requiring timely and accurate diagnosis to improve patient outcomes. Traditional diagnostic methods heavily rely on radiologists' expertise to interpret Magnetic Resonance Imaging (MRI) scans, which can be time-consuming, subjective, and prone to human error. Additionally, the increasing volume of medical imaging data presents a significant challenge to healthcare professionals, often leading to diagnostic delays and variability in results

.Manual analysis of MRI scans may not always ensure consistent accuracy due to the complexity of brain tumor morphology, subtle variations in tumor appearance, and overlapping characteristics with healthy tissues. Furthermore, the classification of brain tumors into different types (e.g., glioma, meningioma, pituitary tumor) is critical for selecting the appropriate treatment strategy, but it requires highly specialized knowledge and experience

.In recent years, artificial intelligence (AI) and machine learning (ML) techniques have shown promising potential in automating and enhancing medical image analysis. These methods can learn from large datasets, detect complex patterns, and classify images with high accuracy and consistency. However, despite advancements, there are still challenges in developing robust, generalizable, and interpretable AI models for brain tumor classification.

This project addresses the need for a reliable, automated system that utilizes machine learning algorithms to assist in the classification of brain tumors using MRI scans. The primary goal is to design and evaluate a model that can accurately classify different types of brain tumors, thereby supporting radiologists in early diagnosis and decision-making, reducing diagnostic time, and improving treatment planning.

Literature overview

Brain Tumor (Brain Cancer)

Cancer is one of the most common diseases worldwide, with an estimated 1.8 million new cases and more than 600,000 deaths in 2020 in the United States alone. Cancer is a disease characterized by the uncontrolled growth of abnormal cells in the body. It is caused by mutations or changes in the function of cells, which leads to the loss of the cell's ability to undergo programmed cell death. This results in the formation of tumors and affects various organs and tissues. Cancer can be difficult to detect depending on the affected organ or cause treatment complications. For example, brain cancer involves CNS parts, making it difficult to perform surgery or radiotherapy to remove the affected regions.

Brain tumors, while they rarely spread to other parts of the body, can still be dangerous as they can grow quickly and damage brain tissue as they diffuse to nearby areas. The growth can press on brain tissue, causing high-impact complications even if the tumors are benign. Brain tumors account for approximately 2.17 % of all cancer deaths and the five-year survival rate is low, at around 5.6 % for glioblastoma. The impact of brain tumors and the concerning statistics have motivated ongoing research in the field, with physicians and scientists searching for ways to prevent tumors, more efficient treatments, better diagnostic tests, and better ways to study and classify tumors. This research includes new methods for exploring brain anatomy and the development of AI systems.

Several tools can be used to detect brain abnormalities such as computed tomography (CT), positron emission tomography (PET), magnetoencephalography (MEG) and magnetic resonance imaging (MRI) are among the most used. MRI is considered the most popular and effective method for detecting brain abnormalities because it can distinguish between different structures and tissues and it does not use ionizing radiation, making it safe for patients [19]. AI has been applied in the field of brain tumor detection, classification, segmentation, diagnosis, and evolution. The application of AI, especially DL-based methods, has demonstrated high levels of accuracy comparable to that of expert radiologists.

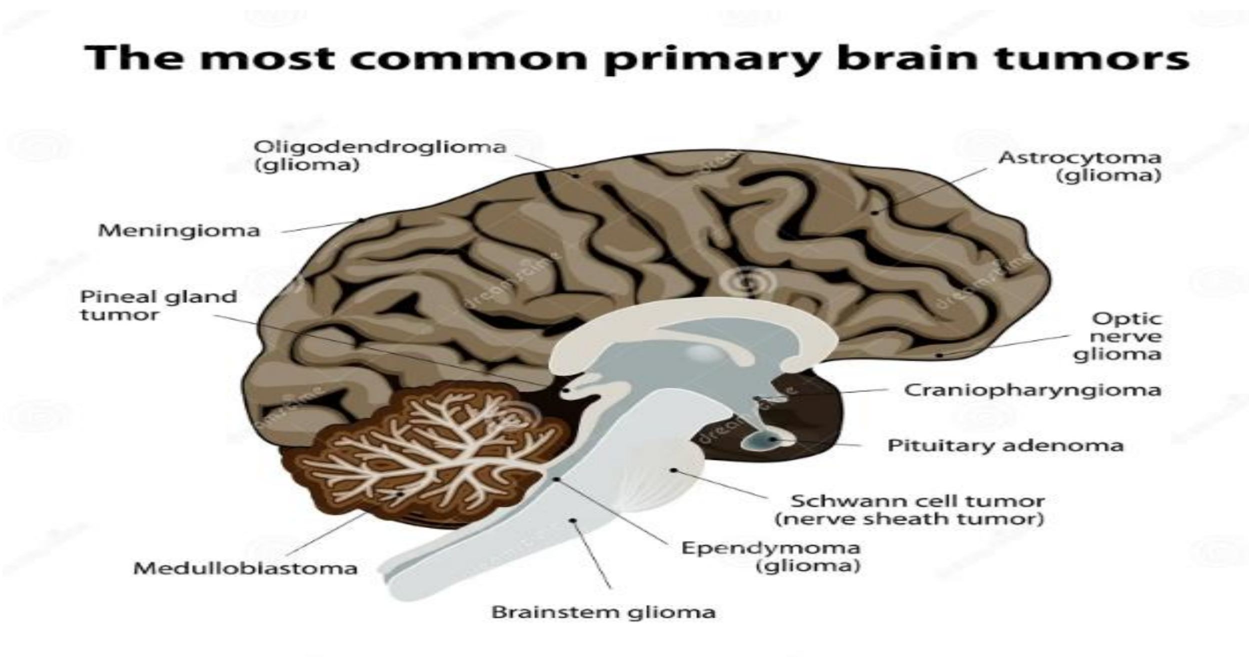


Fig. 1: the most common primary brain tumor.

AI for Medical Diagnosis concept

Artificial Intelligence (AI) in medical diagnosis refers to the application of intelligent computational systems that mimic human reasoning to identify, analyze, and interpret complex medical data for the purpose of detecting diseases and assisting in clinical decision-making. AI systems are designed to learn from historical data, recognize patterns, and make predictions or classifications that aid healthcare professionals in diagnosing conditions more accurately and efficiently.

In the context of modern medicine, diagnostic procedures often involve analyzing vast amounts of data, including medical images, laboratory results, clinical notes, and patient histories. The sheer volume and complexity of this data can exceed human cognitive capabilities, leading to diagnostic errors, delays, or inconsistencies. AI addresses these challenges by providing data-driven, evidence-based tools that enhance the speed, accuracy, and objectivity of medical diagnoses.Accurate and early diagnosis of diseases is still a challenge in healthcare. Recognizing medical conditions and their symptoms is a complex problem. AI can assist clinicians with its data processing capabilities to save time and improve accuracy.

Feature extraction

is a critical step in the development of AI-based systems for medical diagnosis. It involves identifying, selecting, and transforming relevant information from raw medical data (such as images or signals) into a structured format that can be effectively processed by machine learning algorithms.

In medical imaging, such as MRI-based brain tumor classification, feature extraction focuses on converting complex image data into meaningful numerical representations (features) that describe the characteristics of tissues, lesions, or tumors. These features enable AI models to distinguish between different types of abnormalities and make accurate diagnostic predictions.

Brain tumor MRI classification concept

With the rapid development of wearable intelligent and artificial intelligence technologies, per- formance analysis in brain tumor MRI classification has undergone major changes in recent years. Manali Gupta and Sanjay Kumar (2023) stated that in general, to identify pathological conditions in the brain, there exist various medical imaging technologies. Magnetic Resonance Imaging (MRI) is extensively used in medical imaging due to its excellent image quality and independence from ionizing radiations. The significance of deep learning, a subset of artificial intelligence in the area of medical diagnosis applications, has macadamized the path in rapid developments for brain tumor detection from MRI to higher prediction rate. For brain tumor analysis and classification, the convolution neural network (CNN) is the most extensive and widely used deep learning algorithm. In this work, we present a comparative performance analysis of transfer learning-based CNN-pretrained VGG-16, ResNet-50, and Inception-v3 models for automatic prediction of tumor cells in the brain. Pretrained models are demonstrated on the MRI brain tumor images dataset consisting of 233 images. Our paper aims to locate brain tumors with the utilization of the VGG-16 pretrained CNN model. The performance of our model will be evaluated on accuracy. As an outcome, we can estimate that the pretrained model VGG-16 determines highly adequate results with an increase in the accuracy rate of training and validation.

Hassan Ali Khan and Wu Jue (2020) introduced the field of deep learning has helped the health industry in Medical Imaging for Medical Diagnostic of many diseases. For Visual learning and Image Recognition, task CNN is the most prevalent and commonly used machine learning algorithm. Similarly, in our paper, we introduce the convolutional neural network (CNN) approach along with Data Augmentation and Image Processing to categorize brain MRI scan images into cancerous and non-cancerous. Using the transfer learning approach, we compared the performance of our scratched CNN model with pre-trained VGG-16, ResNet-50, and Inception-v3 models. As the experiment is tested on a very small dataset but the experimental result shows that our model accuracy result is very effective and have very low complexity rate by achieving 100% accuracy, while VGG-16 achieved 96%, ResNet-50 achieved 89% and Inception-V3 achieved 75% accuracy. Our model requires very less computational power and has much better accuracy results as compared to other pre-trained models. Sensors and data acquisition methods.

Brain Tumor MRI Classification

Said and Kim identified a Magnetic Resonance Image (MRI) serves as a non-invasive tool to detect the presence of a tumor. However, Rician noise is inevitably instilled during the image acquisition process, which leads to poor observation and interferes with the treatment. Computer-Aided Diagnosis (CAD) systems can perform early diagnosis of the disease, potentially increasing the chances of survival, and lessening the need for an expert to analyze the MRIs. Convolutional Neural Networks (CNN) have proven to be very effective in tumor detection in brain MRIs. There have been multiple studies dedicated to brain tumor classification; however, these techniques lack the evaluation of the impact of the Rician noise on state-of-the-art deep learning techniques and the consideration of the scaling impact on the performance of the deep learning as the size and location of tumors vary from image to image with irregular shape and boundaries. Moreover, transfer learning-based pre-trained models such as AlexNet and ResNet have been used for brain tumor detection. However, these architectures have many trainable parameters and hence have a high computational cost. This study proposes a two-fold solution: (a) Multi-Scale CNN (MSCNN) architecture to develop a robust classification model for brain tumor diagnosis, and (b) minimizing the impact of Rician noise on the performance of the MSCNN. The proposed model is a multi-class classification solution that classifies MRIs into glioma, meningioma, pituitary, and non-tumor. The core objective is to develop a robust model for enhancing the performance of the existing tumor detection systems in terms of accuracy and efficiency. Furthermore, MRIs are denoised using a Fuzzy Similarity-based Non-Local Means (FSNLM) filter to improve the classification results. Different evaluation metrics are employed, such as accuracy, precision, recall, specificity, and F1-score, to evaluate and compare the performance of the proposed multi-scale CNN and other state-of-the-art techniques, such as AlexNet and ResNet. In addition, trainable and non-trainable parameters of the proposed model and the existing techniques are also compared to evaluate the computational efficiency. The experimental results show that the proposed multi-scale CNN model outperforms AlexNet and ResNet in terms of accuracy and efficiency at a lower computational cost. Based on experimental results, it is found that our proposed MCNN2 achieved accuracy and F1-score of 91.2% and 91%, respectively, which is significantly higher than the existing AlexNet and ResNet techniques. Moreover, our findings suggest that the proposed model is more effective and efficient in facilitating clinical research and practice for MRI classification.

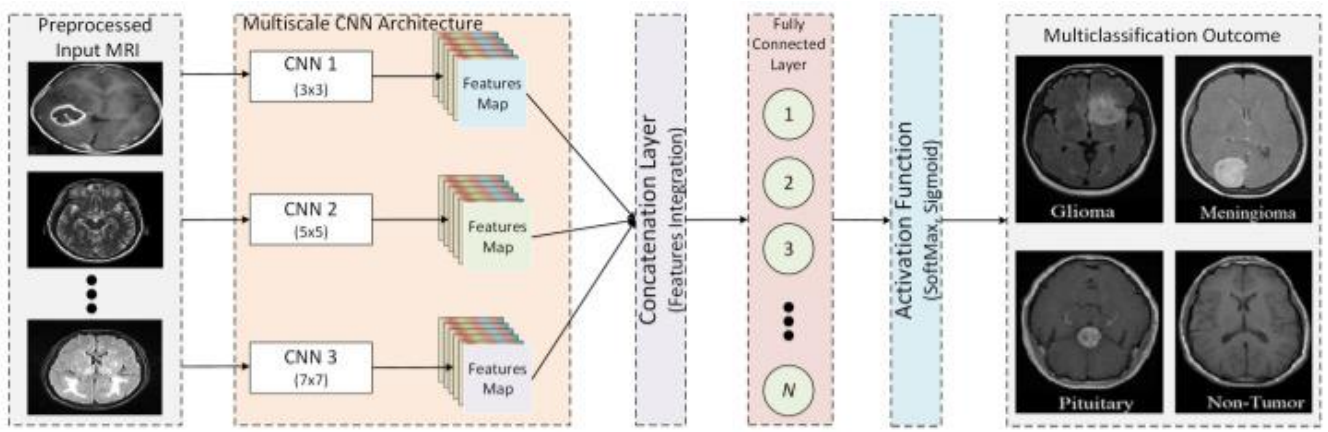


Fig. 2: Block model of the proposed multi-scale CNN architecture. (Said & Kim, 2022)

Yuting and Fulvio The main objective of this work is to present a comprehensive review of studies using CNN architectures to classify brain tumors using MR images with the aim of identifying useful strategies for and possible impediments in the development of this technology. Relevant articles were identified using a predefined, systematic procedure. For each article, data were extracted regarding training data, target problems, the network architecture, validation methods, and the reported quantitative performance criteria. The clinical relevance of the studies was then evaluated to identify limitations by considering the merits of convolutional neural networks and the remaining challenges that need to be solved to promote the clinical application and development of CNN algorithms. Finally, possible directions for future research are discussed for researchers in the biomedical and machine learning communities. A total of 83 studies were identified and reviewed. They differed in terms of the precise classification problem targeted and the strategies used to construct and train the chosen CNN. Consequently, the reported performance varied widely, with accuracies of 91.63–100% in differentiating meningiomas, gliomas, and pituitary tumors (26 articles) and of 60.0–99.46% in distinguishing low-grade from high-grade gliomas (13 articles). The review provides a survey of the state of the art in CNN-based deep learning methods for brain tumor classification. Many networks demonstrated good performance, and it is not evident that any specific methodological choice greatly outperforms the alternatives, especially given the inconsistencies in the reporting of validation methods, performance metrics, and training data encountered. Few studies have focused on clinical usability.

Feature extraction

Machine learning requires a very large amount of data. Especially, when the dimension of the data increases significantly the data required for an accurate analysis increases dramatically. is a crucial step in the machine learning process for brain tumor MRI classification. It involves identifying and quantifying important characteristics from MRI scans that help distinguish between different types of brain tumors such as glioma, meningioma, and pituitary tumors. These features can include intensity-based information (such as pixel brightness), texture patterns (like those derived from Gray Level Co-occurrence Matrices or Local Binary Patterns), shape attributes (including area and compactness), and frequency-based characteristics using techniques like wavelet transforms. Effective feature extraction reduces data complexity while preserving essential diagnostic information, allowing machine learning models to learn and classify tumor types more accurately. By focusing on the most relevant features, this process enhances model performance and contributes to more reliable and automated brain tumor diagnosis.

Drawbacks and challenges

Despite the significant progress in applying machine learning to brain tumor MRI classification, several drawbacks and challenges remain that affect the accuracy, reliability, and clinical adoption of these systems.

1. Limited and Imbalanced Datasets

One of the primary challenges is the availability of large, high-quality, and annotated MRI datasets. Brain tumors are relatively rare, and collecting labeled data requires expert radiologists, which is both time-consuming and expensive. Additionally, many datasets suffer from class imbalance—some tumor types may have far fewer samples than others, leading to biased model performance.

2. Variability in MRI Scans

MRI scans can vary significantly across different scanners, imaging protocols, and institutions. Variations in resolution, contrast settings, and noise levels can affect the consistency of the features extracted, making it difficult to develop models that generalize well to new data.

3. Tumor Heterogeneity

Brain tumors often exhibit high intra-class variability in terms of size, shape, location, and intensity. This heterogeneity makes it challenging to extract consistent features and accurately classify tumors. Even tumors of the same type can appear quite different in MRI images.

4. Overfitting and Generalization

Machine learning models, particularly deep learning approaches, are prone to overfitting when trained on small datasets. While they may perform well on training data, their performance on unseen or external data can degrade significantly, limiting clinical applicability.

5. Segmentation Dependence

Many classification approaches rely on accurate tumor segmentation prior to feature extraction. Errors in segmentation—especially in automated or semi-automated methods—can lead to incorrect features and poor classification results.

6. Interpretability and Trust

Machine learning models, especially deep neural networks, are often seen as "black boxes" because their decision-making process is not easily interpretable. In medical applications, lack of transparency can hinder trust among clinicians and delay the integration of AI systems into clinical workflows.

7. Computational Complexity

Advanced models, especially 3D deep learning architectures used for MRI volumes, can be computationally intensive. This poses challenges in terms of training time, hardware requirements, and deployment in resource-limited settings such as smaller hospitals.

According to Borko, at the book, Multimedia Tools and Applications say Brain tumor classification (BTC) using magnetic resonance imaging (MRI) are very important for the early detection of brain tumors (BTs). It makes a substantial contribution to improving the accuracy of medical evaluations and treatment approaches, which eventually results in better patient outcomes. Neural networks (NNs) techniques, like deep learning (DL), machine learning (ML), and transfer learning (TL) have recently shown promise as tools for automating and enhancing procedures for BTC. This review critically evaluates the present research on NN-based techniques for BTC, emphasizing its advantages, disadvantages, and potential for future development. The variability and variety of physical features of tumors make it difficult to classify BTs. Conventional diagnostic procedures often lack the accuracy necessary for correct classification, which may result in therapy delays and subpar patient care. The primary aim of this research is to assess the efficacy of current neural network approaches in addressing the challenges associated with identifying and classifying the various forms of brain tumors. Additionally, we want to compare these techniques in order to determine the most effective approach. We comprehensively examine several NN designs after conducting an extensive literature study. According to our study findings, neural network techniques consistently demonstrate superior performance in the classification of brain tumor's when compared to conventional methodologies often used in the field. Future prospects lie in the development of novel architectures, the inclusion of data from multiple sources, and incorporation of explainable AI techniques. By addressing these challenges, NN can pave the way for more accurate, efficient, and personalized BTC, ultimately contributing to better clinical outcomes and advancing our understanding of brain pathology. The results of this research will perform as a benefit starting point for future studies.

Methods, applications, and results in Brain Tumor MRI

A convolutional neural network (CNN) is a deep learning approach that has frequently been applied to medical imaging problems. It overcomes the limitations of previous deep learning approaches because its architecture allows it to automatically learn the features that are important for a problem using a training corpus of sufficient variety and quality. Recently, CNNs have gained popularity for brain tumor classification due to their outstanding performance with very high accuracy. Despite the growing interest in CNN-based CADx within the research community, translation into daily clinical practice has yet to be achieved due to obstacles such as the lack of an adequate amount of reliable data for training algorithms and imbalances within the datasets used for multi-class classification, among others. Several reviews have been published in this regard, summarizing the classification methods and key achievements and pointing out some of the limitations in previous studies, but as of yet, none of them have focused on the deficiencies regarding clinical adoption or have attempted to determine the future research directions required to promote the application of deep learning models in clinical practice. For these reasons, the current review considers the key limitations and obstacles regarding the clinical applicability of studies in brain tumor classification using CNN algorithms and how to translate CNN-based CADx technology into better clinical decision making.
In this review, we explore the current studies on using CNN-based deep learning techniques for brain tumor classification published between 2015 and 2022. We decided to focus on CNN

architectures, as alternative deep-learning techniques, such as
Deep Belief Networks or Restricted Boltzmann Machines, are much less represented in the current literature.

Yuting and Fulvio As mentioned in the introduction, many CNN models have been used to classify the MR images of brain tumor patients. They overcome the limitations of earlier deep learning approaches and have gained popularity among researchers for brain tumor classification tasks. shows the number of research articles on brain tumor classification using deep learning methods and CNN-based deep learning techniques published on PubMed and Scopus in the years from 2015 to June 2022; the number of papers related to brain tumor classification using CNN techniques grows rapidly from 2019 onwards and accounts for the majority of the total number of studies published in 2020, 2021, and 2022. This is because of the high generalizability, stability, and accuracy rate of CNN algorithms.

AlexNet [85] came out in 2012 and was a revolutionary advancement in deep learning; it improved traditional CNNs by introducing a composition of consecutively stacked convolutional layers and became one of the best models for image classification. VGG, which refers to the Visual Geometry Group, was a breakthrough in the world of convolutional neural networks after AlexNet. It is a type of deep CNN architecture with multiple layers that was originally proposed by K. Simonyan and A. Zisserman in [86] and was developed to improve model performance by increasing the depth of such CNNs.

GoogLeNet is a deep convolutional neural network with 22 layers based on the Inception architecture; it was developed by researchers at Google [87]. GoogLeNet addresses most of the problems that large networks face, such as computational expense and overfitting, by employing the Inception module. This module can use max pooling and three varied sizes of filters (1×1, 3×3, 5×5) for convolution in a single image block; such blocks are then concatenated and passed onto the next layer. An extra 1×1 convolution can be added to the neural network before the 3×3 and 5×5 layers to make the process even less computationally expensive [87]. ResNet stands for Deep Residual Network. It is an innovative convolutional neural network that was originally proposed in [88]. ResNet makes use of residual blocks to improve the accuracy of models. A residual block is a skip-connection block that typically has double- or triple-layer skips that contain nonlinearities (ReLU) and batch normalization in between; it can help to reduce the problem of vanishing gradients or can help to mitigate accuracy saturation problems [88]. DenseNet, which stands for Dense

Convolutional Network, is a type of convolutional neural network that utilizes dense connections between layers. DenseNet was mainly developed to improve the decreased accuracy caused by the vanishing gradient in neural networks [89]. Additionally, those CNNs take in images with a pixel resolution of 224 × 224. Therefore, for brain tumor classification, the authors need to center crop a 224 × 224 patch in each image to keep the input image size consistent.

Convolutional neural networks are commonly built using a fixed resource budget. When more resources are available, the depth, width, and resolution of the model need to be scaled up for better accuracy and efficiency [90]. Unlike previous CNNs, EfficientNet is a novel baseline network that uses a different model-scaling technique based on a compound coefficient and neural architecture search methods that can carefully balance network depth, width, and resolution [90].

the factors that hinder the adoption and development of CNN-based brain tumor classification CADx systems into clinic practice, including data quality, data scarcity, data mismatch, data imbalance, classification performance, research value towards clinic needs, and the Black-Box characteristics of CNN models.

Data Quality During the MR image acquisition process, both the scanner and external sources may produce electrical noise in the receiver coil, generating image artifacts in the brain MR volumes [69]. In addition, the MR image reconstruction process is sensitive to acquisition conditions, and further artifacts are introduced if the subject under examination moves during the acquisition of a single image [69]. These errors are inevitable and reduce the quality of the MR images used to train networks. As a result, the quality of the training data degrades the sensitivity/specificity of CNN models, thus compromising their applicability in a clinic setting.

Data Scarcity and Big data is one of the biggest challenges that CNN-based CADx systems face today. A large number of high-quality annotated data is required to build high-performance CNN classification models, while it is a challenge to label a large number of medical images due to the complexity of medical data. When a CNN classification system does not have enough data, overfitting can occur—as classification is based on extraneous variance in the training set—affecting the capacity of the network to generalize new data [91].

Data Mismatch refers to a situation in which a model that has been well-trained in a lab environment fails to generalize real-world clinical data. It might be caused by overfitting of the training set or due to mismatch between research images and clinic ones [82].

Studies are at high risk of generalization failure if they omit a validation step or if the test set does not reflect the characteristics of the clinical data.

Class Imbalance in brain MRI datasets such as the BraTS 2019 dataset [**92**], which consists of 210 HGG and 75 LGG patients ,HGG is represented by a much higher percentage of samples than LGG, leading to so-called class imbalance problems, in which inputting all of the data into the CNN classifier to build up the learning model will usually lead to a learning bias to the majority class [**93**]. When an unbalanced training set is used, it is important to assess model performance using several performance measures.

The authors in [**100**] used different data augmentation methods, including rotation, flipping, Gaussian blur, sharpening, edge detection, embossing, skewing, and shearing, to increase the size of the dataset. The proposed system aims to classify between Grade I, Grade II, Grade III, and Grade IV, and the original data consist of 121 images (36 Grade I images, 32 Grade II images, 25 Grade III images, and 28 Grade IV images), and by using data augmentation techniques, 30 new images are generated from each MR image. The proposed model is experimentally evaluated using both augmented and original data. The results show that the overall accuracy after data augmentation reaches 90.67%, which is greater than the accuracy of 87.38% obtained without augmentation.

While most data augmentation techniques aim to increase extraneous variance in the training set, deep learning can be used by itself, at least in theory, to increase meaningful variance. In a recent publication by Allah et al. [**44**], a novel data augmentation method called a progressive growing generative adversarial network (PGGAN) was proposed and combined with rotation and flipping methods. The method involves an incremental increase of the size of the model during the training to produce MR images of brain tumors and to help overcome the shortage of images for deep learning training. The brain tumor images were classified using a VGG19 feature extractor coupled with a CNN classifier. The accuracy of the combined VGG19 + CNN and PGGAN data augmentation framework achieved an accuracy of 98.54%.

Thesis introduction

Concepts

Brain tumors are among the most life-threatening medical conditions, with early and accurate diagnosis being critical for effective treatment and patient survival. According to the World Health Organization (WHO), brain tumors account for approximately 2% of all cancer-related deaths globally, with malignant tumors posing a significant challenge due to their aggressive nature. Magnetic Resonance Imaging (MRI) is the primary diagnostic tool for detecting brain tumors, as it provides high-resolution images of brain tissues without invasive procedures. However, manual interpretation of MRI scans by radiologists is time-consuming, subjective, and prone to human error, especially in cases where tumors are small or exhibit subtle abnormalities.

The rapid advancements in Artificial Intelligence (AI) and Machine Learning (ML) have opened new possibilities for automating medical image analysis, improving diagnostic accuracy, and reducing the workload on healthcare professionals. In particular, Convolutional Neural Networks (CNNs), a class of deep learning models, have demonstrated remarkable success in image classification tasks due to their ability to automatically extract and learn hierarchical features from medical images. Applying CNNs to brain tumor MRI classification can enhance diagnostic precision, reduce interpretation time, and assist radiologists in making more informed clinical decisions.

This thesis focuses on developing and evaluating CNN-based models for the automated classification of brain tumors using MRI scans. The study explores both custom CNN architectures and transfer learning approaches using pre-trained models such as VGG16, ResNet, and EfficientNet. The goal is to compare their performance in distinguishing between different tumor types (glioma, meningioma, pituitary) and normal brain tissue, ultimately contributing to more efficient and reliable diagnostic tools in neuroimaging.

CNN Model Classification

Convolutional Neural Networks (CNNs) are a specialized class of deep learning models designed primarily for image classification and computer vision tasks. Unlike traditional neural networks, CNNs leverage spatial hierarchies by automatically learning features through convolutional layers, making them exceptionally effective for processing pixel-based data. The classification process in CNNs involves multiple stages, including feature extraction, dimensionality reduction, and final classification using fully connected layers classify images by progressively extracting higher-level features through a series of convolutional and pooling layers. The initial layers detect simple patterns like edges and textures, while deeper layers recognize complex structures such as shapes and objects. The final layers convert these features into class probabilities using a SoftMax activation function, assigning the input image to one of the predefined categories. CNN-based classification has revolutionized computer vision, enabling machines to interpret visual data with human-like accuracy. By leveraging deep architectures and optimization techniques, CNNs continue to advance fields like healthcare, robotics, and AI-driven automation. Future research will focus on making these models faster, more efficient, and accessible for real-world applications .

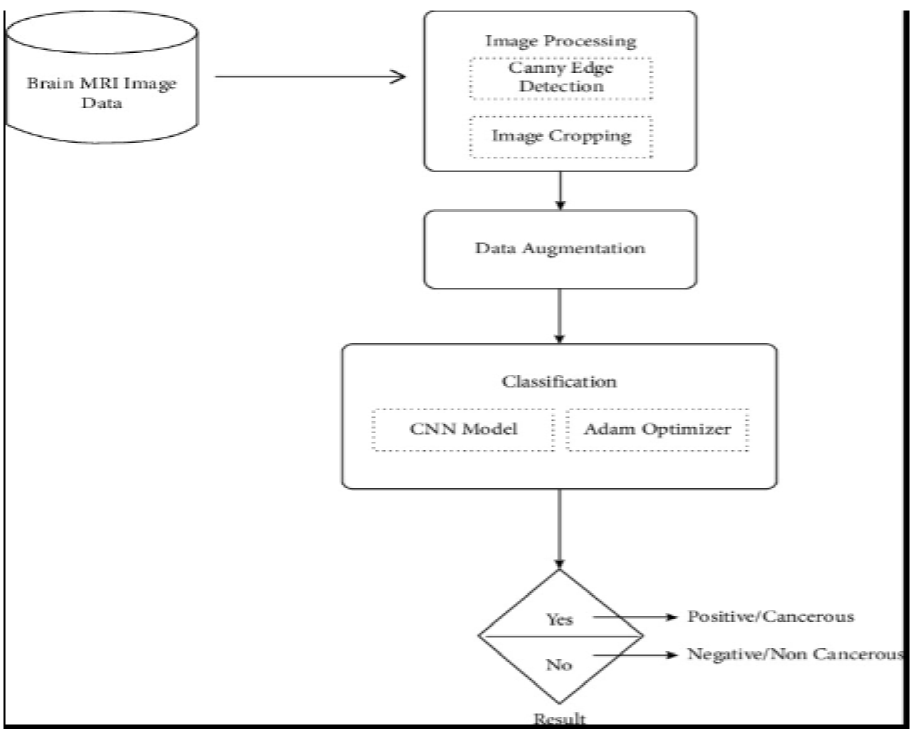


Fig. 3: Example of Convolutional Neural Networks (CNNs)

Model validation and objectives

Validation is a critical step in developing Convolutional Neural Networks (CNNs) to ensure the model generalizes well to unseen data. Unlike traditional machine learning models, CNNs require specialized validation techniques due to their complex architectures and high-dimensional input data.

The authors in [**118**] proposed a 3D CNN model for brain tumor classification between GBM, AST, and OLI. A merged dataset comprising data from the CPM-RadPath 2019 and BraTS 2019 databases was used to train and validate the proposed model, but the authors did not perform image co-registration. The results show that the classification model has very poor performance during brain tumor classification, with an accuracy of 74.9%.

In [**135**], the researchers presented a CNN-PSO method for two classification tasks: normal vs. Grade II vs. Grade III vs. Grade IV and MEN vs. glioma vs. PA. The MR images used for the first task were collected from four publicly available datasets: the IXI dataset, REMBRANDT, TCGA-GBM, and TCGA-LGG. The overall accuracy obtained was 96.77% for classification between normal, Grade II, Grade III, and Grade IV and 98.16% for MEN, glioma, and PA classification.

Similar to the work conducted in [**135**], Anaraki et al. [**136**] used MR data merged from four online databases: the IXI dataset, REMBRANDT, TCGA-GBM, and TCGA-LGG, and from one private dataset collected by the authors for normal, Grade II, Grade III, and Grade IV classification. They also used the dataset proposed by Cheng [**55**] for MEN, glioma, and PA classification. Different data augmentation methods were performed to further enlarge the size of the training set. The authors in these studies did not co-register the MR images from different sequences from different institutions for the four-class classification task. The results show that 93.1% accuracy was achieved for normal, Grade II, Grade III, and Grade IV classification, and 94.2% accuracy was achieved for MEN, glioma, and PA classification.

Despite the high accuracy levels reported in most studies using CNN techniques, we found that in several studies [**102**,**117**,**118**,**137**], the models demonstrated very poor performance during brain tumor classification tasks.

The authors in [102] explored transfer learning techniques for brain tumor classification. The experiments were performed on the BraTS 2019 dataset, which consists of 335 patients diagnosed with brain tumors (259 patients with HGG and 76 patients with LGG). The model achieved a classification AUC of 82.89% on a separate test dataset of 66 patients. The classification performance obtained by transfer learning in this study is relatively low, hindering its development and application in clinical practice. The authors of [117] presented a 3D CNN model developed to categorize adult diffuse glioma cases into the OLI and AST classes. The dataset used in the experiment consisted of 32 patients (16 patients with OLI and 16 patients with AST). The model achieved accuracy values of 80%. The main reason for the poor performance probably lies in the small dataset, with only 32 patients being used for model training. That is far from enough to train a 3D model.

In another study [137], two brain tumor classification tasks were studied using the Lenet, AlexNet, and U-net CNN architectures. In the experiments, MR images from 11 patients (two metastasis, six glioma, and three MEN) obtained from Radiopaedia were utilized to classify metastasis, glioma, and MEN; the data of 20 patients collected from BraTS 2017 were used for HGG and LGG classification. The results show poor classification performance by the three CNN architectures on the two tasks, with an accuracy of 75% obtained by AlexNet and an accuracy of 48% obtained by Lenet for the first task and an accuracy of 62% obtained by AlexNet and an accuracy of 60% obtained by U-net for the second task. The poor performance of Lenet is probably due to its simple architecture, which is not capable of high-resolution image classification. On the other hand, the U-net CNN performs well in segmentation tasks but is not the most commonly used network for classification.

Even though CNNs have demonstrated remarkable performance in brain tumor classification tasks in the majority of the reviewed studies, their level of trustworthiness and transparency must be evaluated in a clinic context. Of the included articles, only two studies, conducted by Artzi et al. [122] and Gaur et al. [127], investigated the Black-Box nature of CNN models for brain tumor classification to ensure that the model is looking in the correct place rather than at noise or unrelated artifacts.

The authors in [122] proposed a pre-trained ResNet-50 CNN architecture to classify three posterior fossa tumors from a private dataset and explained the classification decision by using gradient-weighted class activation mapping (Grad-CAM). The dataset consisted of 158 MRI scans of 22 healthy controls and 63 PA, 57 MB, and 16 EP patients. In this study, several preprocessing methods were used to reduce the influence of MRI data on the classification performance of the proposed CNN model. Image co-registration was performed to ensure that the images become spatially aligned. Bias field correction was also conducted to remove the intensity gradient from the image. Data augmentation methods, including flipping, reflection, rotation, and zooming, were used to increase the size and diversity of the dataset.

However, class imbalance within the dataset, particularly the under-representation of EP, was not addressed. The proposed architecture achieved a mean validation accuracy of 88% and 87% for the test dataset. The results demonstrate that the proposed network using Grad-CAM can identify the area of interest and train the classification model based on pathology-related features.

Gaur et al. [**127**] proposed a CNN-based model integrated with local interpretable model-agnostic explanation (LIME) and Shapley additive explanation (SHAP) for the classification and explanation of meningioma, glioma, pituitary, and normal images using an MRI dataset of 2870 MR images. For better classification results, Gaussian noise was introduced in the pre-processing step to improve the learning for the CNN, with mean = 0 and a standard deviation of $10^{0.5}$. The proposed CNN architecture achieved an accuracy of 94.64% for the MRI dataset. The proposed model also provided a locally model-agnostic explanation to describe the results for ordinary people more qualitatively.

Dataset

Dataset Importance and method

Early detection and classification of brain tumors is an important research domain in the field of medical imaging and accordingly helps in selecting the most convenient treatment method to save patients life therefore. The application of deep learning approaches in context to improve health diagnosis is providing impactful solutions. According to the World Health Organization (WHO), proper brain tumor diagnosis involves detection, brain tumor location identification, and classification of the tumor on the basis of malignancy, grade, and type. This experimental work in the diagnosis of brain tumors using Magnetic Resonance Imaging (MRI) involves detecting the tumor, classifying the tumor in terms of grade, type, and identification of tumor location. This method has experimented in terms of utilizing one model for classifying brain MRI on different classification tasks rather than an individual model for each classification task. The Convolutional Neural Network (CNN) based multi-task classification is equipped for the classification and detection of tumors. The identification of brain tumor location is also done using a CNN-based model by segmenting the brain tumor.

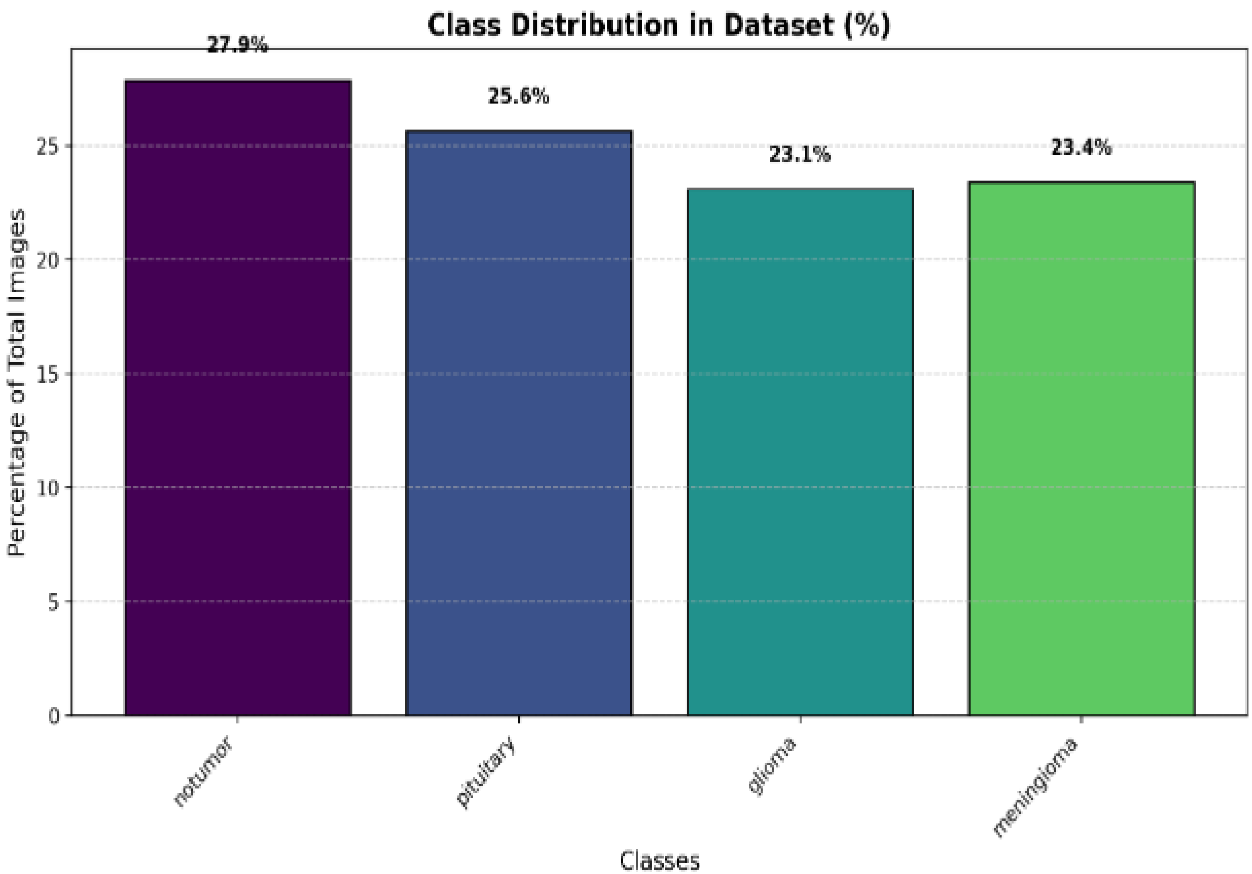
This dataset consists of 7,023 human brain MRI images, categorized into four distinct classes: glioma, meningioma, no tumor, and pituitary tumor. Each class represents a critical diagnostic category in medical imaging:

Glioma – Tumors originating from glial cells, often aggressive and requiring early detection.

Meningioma – Typically benign tumors growing from meninges, the protective layers of the brain.

No Tumor – Healthy brain scans serving as negative controls for classification.

Pituitary Tumor – Abnormal growths in the pituitary gland, affecting hormone regulation.



Figer.4 class distributions in dataset%

class distribution analysis of a dataset, brain tumor MRI classes. The data is divided into four categories.

structured breakdown of the Brain Tumor MRI dataset, clearly separating the distribution of images between training and testing sets across four diagnostic classes: Pituitary, No Tumor, Meningioma, and Glioma.

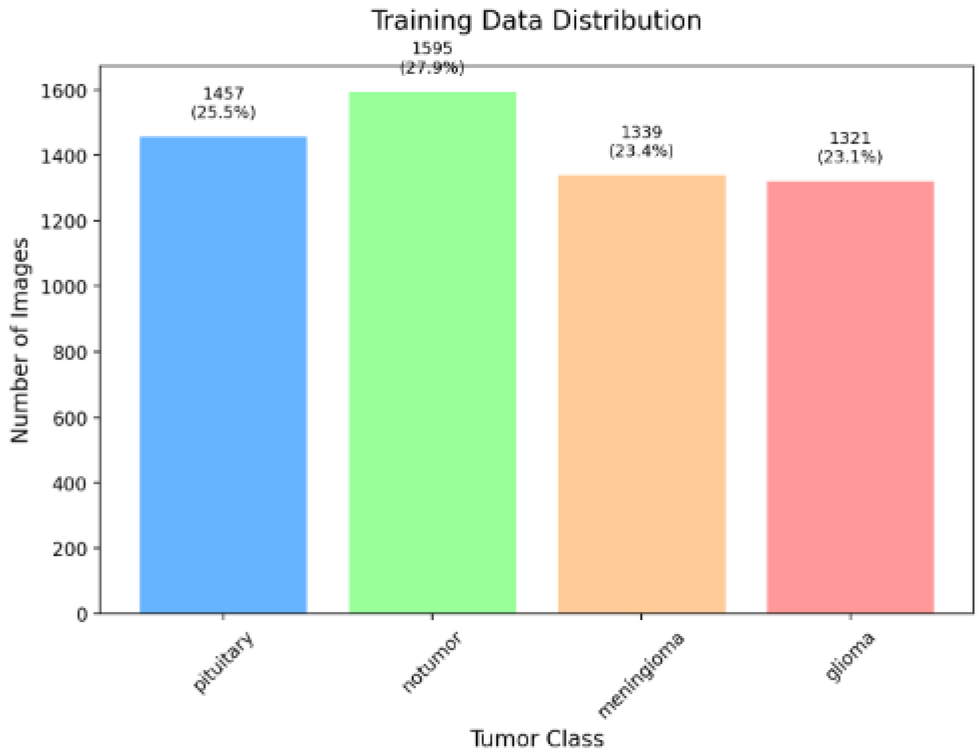


Fig. 5: Training data distribution

Training Set (5,712 images, 81.3% of total):

The largest class is "No Tumor" (27.92%), followed by Pituitary (25.51%), Meningioma (23.44%), and Glioma (23.13%).

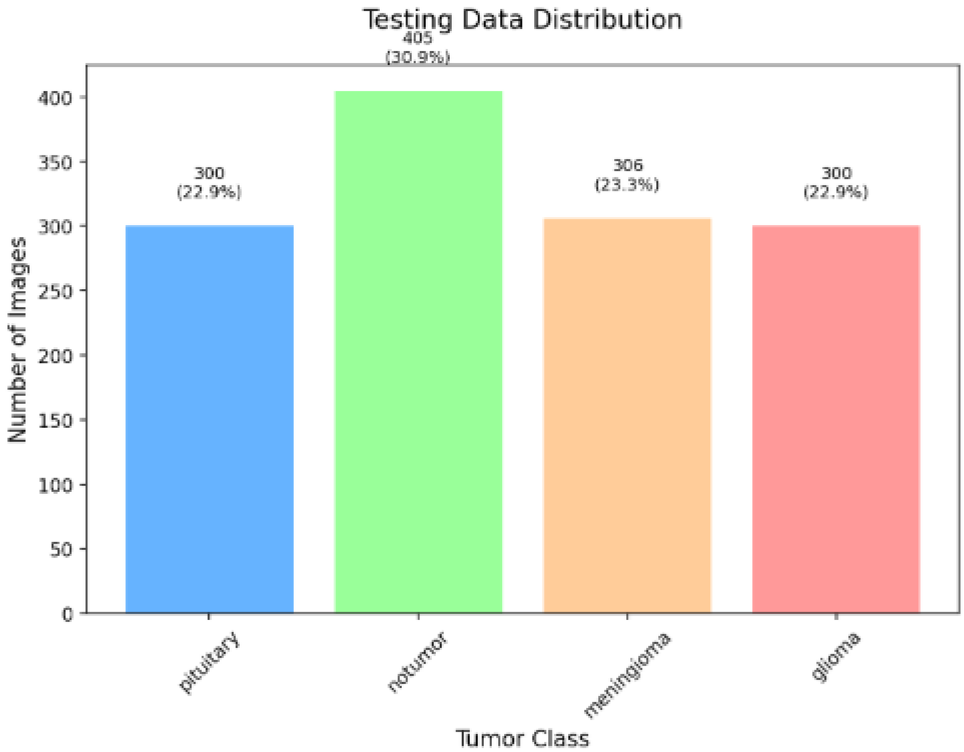


Fig. 6: testing data distribution

Testing Set (1,311 images, 18.7% of total):

Proportions align closely with the training set (e.g., "No Tumor" rises slightly to 30.89%, while others stay near ~22–23%).

Train-Test Split Visualization

the train-test split distribution of a dataset, showing a clear division between training data (81.3%) and testing data (18.7%). This split follows a common machine learning practice where the majority of data is allocated for training the model, while a smaller, independent portion is reserved for evaluating its performance on unseen examples.

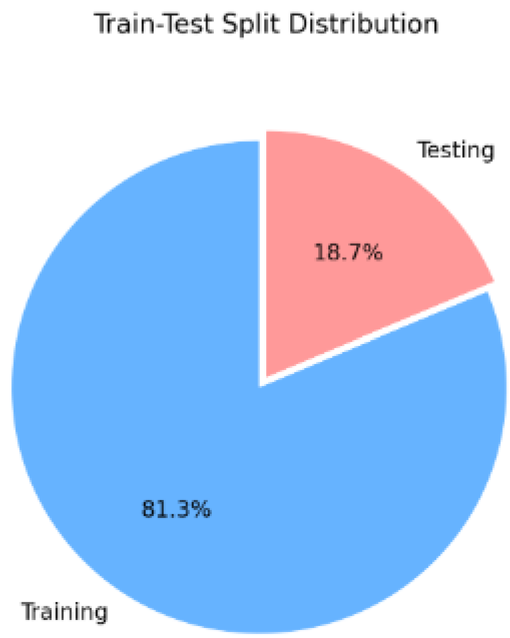


Fig. 7: train-test data distribution

Training Data Dominance (81.3%):

The large training proportion ensures the model has sufficient examples to learn meaningful patterns,

Testing Data (18.7%):

The ~19% held-out set provides a robust benchmark to assess model accuracy without overfitting.

dataset composition

The dataset composition table reveals a well-structured 81.3%-18.7% train-test split of 7,023 brain MRI images, demonstrating careful attention to maintaining class distribution integrity across both sets. The training set (5,712 images) and testing set (1,311 images) preserve similar proportional representation across all four diagnostic categories: Pituitary (25.51% train vs 22.86% test), No Tumor (27.92% vs 30.89%), Meningioma (23.44% vs 23.34%), and Glioma (23.13% vs 22.86%). While the "No Tumor" class shows a slight 3% increase in the testing set, the overall distribution remains remarkably consistent, suggesting proper stratified sampling was employed. This balanced partitioning is particularly crucial for medical imaging tasks, as it helps ensure the model's evaluation metrics reliably reflect true diagnostic performance across all tumor types. The minor variations in class proportions (all within ±3%) are unlikely to introduce significant bias, though practitioners might still consider applying class weights during training for optimal minority class (Glioma) performance. The clear documentation of absolute counts alongside percentages enhances reproducibility and allows for precise calculation of augmentation needs or sampling strategies if required.

Brain Tumor MRI Dataset Composition

Class	Training Count	Training %	Testing Count	Testing %	Total
Pituitary	1,457	25.51%	300	22.86%	1,757
No Tumor	1,595	27.92%	405	30.89%	2,000
Meningioma	1,339	23.44%	306	23.34%	1,645
Glioma	1,321	23.13%	300	22.86%	1,621
Total	5,712	100%	1,311	100%	7,023

Fig. 8: Brain Tumor Dataset Composition

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Summary Statistics of Dataset

The dataset exhibits well-balanced statistical distribution across its four diagnostic classes, demonstrating careful curation for machine learning applications. The total collection comprises 7,023 MRI scans, with a conventional 81.3% (5,712 images) allocated for training and 18.7% (1,311 images) reserved for testing. Class distribution remains remarkably consistent between training and testing subsets, with all categories maintaining proportional representation within a narrow ±3% margin. The "notumor" class represents the largest category (2,000 images, 28.5% of total), followed closely by pituitary tumors (1,757, 25.0%), meningiomas (1,645, 23.4%), and gliomas (1,621, 23.1%). This equilibrium in class distribution significantly reduces the need for extensive rebalancing techniques while supporting robust model generalization. The testing set maintains nearly identical class proportions to the training data (e.g., meningioma 23.4% train vs 23.3% test), indicating proper stratified sampling methodology was employed. Such balanced partitioning is particularly valuable for medical imaging tasks, where equitable representation of all diagnostic categories ensures clinically meaningful performance evaluation. Minor variations, such as the 3% increased representation of healthy scans ("notumor") in the test set, fall within acceptable thresholds for most deep learning applications. The dataset's structural integrity suggests it is immediately suitable for convolutional neural network development, with optional consideration given to light class weighting or augmentation strategies to further optimize glioma detection (the smallest class at 23.1%).

=== Dataset Summary Statistics ===

Class	Training Count %	Testing Count %	Total Count
pituitary	1457 (25.5%)	300 (22.9%)	1757
notumor	1595 (27.9%)	405 (30.9%)	2000
meningioma	1339 (23.4%)	306 (23.3%)	1645
glioma	1321 (23.1%)	300 (22.9%)	1621
Total	5712 (100.0%)	1311 (100.0%)	7023

Random Sample Visualization for Dataset

To ensure proper dataset understanding and quality control, we visualize random samples from each class in a 3x4 grid format. Each image displays: (1) the original MRI scan, (2) its preprocessed version, and (3) critical metadata including tumor location (where applicable) and image dimensions. The visualization reveals important characteristics: pituitary tumors typically appear as small, bright masses near the sella turcica; meningiomas show as well-circumscribed dural-based lesions; gliomas demonstrate irregular infiltrative patterns; while healthy scans maintain symmetrical ventricular structures. This qualitative examination serves multiple purposes: verifying correct class labeling, identifying potential artifacts or anomalies, and providing clinicians with intuitive model interpretability. The side-by-side display of raw and preprocessed images helps evaluate the effectiveness of normalization and augmentation techniques while maintaining diagnostic relevance. Such visualization is particularly valuable for detecting dataset biases, confirming tumor annotation accuracy, and establishing face validity before model training.

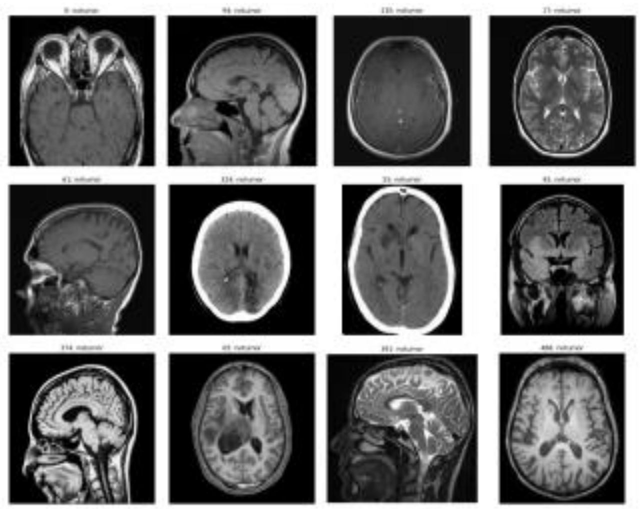

Fig. 9: Random Sample Visualization

Analysis function for CNN

Evaluation Metrics for Multi-Class Classification Tasks

In the case of multi-class classification with four possible outputs, some of the metrics need to be adjusted. Here we explain the metrics for multi-class classification:

A confusion matrix is a table that summarizes the performance of a classification model. Since we have multiple classes for us we will use it to provid a breakdown of predictions versus actual class labels for each class.

In a multi-class system we have:

TP (True Positives): Number of instances correctly classified as a specific class.

FP (False Positives): Number of instances incorrectly classified as a specific class, which do not actually belong to it.

FN (False Negatives): Number of instances belonging to a specific class but incorrectly classified as other classes

Precision

Precision measures the ability of the model to correctly identify positive instances for each class among all instances predicted as positive.

For each class c: Precision_c = TP_c / (TP_c + FP_c)

$$\text{Precision}_c = \frac{\text{TP}_c}{\text{TP}_c + \text{FP}_c}$$

Recall (Sensitivity or True Positive Rate)

Recall calculates the ability of the model to correctly identify positive instances for each class among all actual positive instances.

For each class c: Recall_c = TP_c / (TP_c + FN_c)

$$\text{Recall}_c = \frac{\text{TP}_c}{\text{TP}_c + \text{FN}_c}$$

F1-Score

The F1-score is the harmonic mean of precision and recall. It provides a balanced measure that combines both metrics for each class.

For each class c: F1-Score_c = 2 * (Precision_c * Recall_c) / (Precision_c + Recall_c)

$$\text{F1-Score}_c = 2 \times \frac{\text{Precision}_c \times \text{Recall}_c}{\text{Precision}_c + \text{Recall}_c}$$

Accuracy

Accuracy measures the overall correctness of the model's predictions across all classes. Accuracy = (TP_1 + TP_2 + ... + TP_N) / (TP_1 + TP_2 + ... + TP_N + FP_1 + FP_2 + ... + FP_N + FN_1 + FN_2 + ... + FN_N)

$$\text{Accuracy} = \frac{\text{TP}_1 + \text{TP}_2 + \ldots + \text{TP}_N}{\text{TP}_1 + \text{TP}_2 + \ldots + \text{TP}_N + \text{FP}_1 + \text{FP}_2 + \ldots + \text{FP}_N + \text{FN}_1 + \text{FN}_2 + \ldots + \text{FN}_N}$$

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Architecture of a Convolutional Neural Network (CNN)

Layer (type)	Output Shape	Param #
conv2d_3 (Conv2D)	(None, 222, 222, 32)	896
batch_normalization_3 (BatchNormalization)	(None, 222, 222, 32)	128
max_pooling2d_3 (MaxPooling2D)	(None, 111, 111, 32)	0
conv2d_4 (Conv2D)	(None, 109, 109, 64)	18,496
batch_normalization_4 (BatchNormalization)	(None, 109, 109, 64)	256
max_pooling2d_4 (MaxPooling2D)	(None, 54, 54, 64)	0
conv2d_5 (Conv2D)	(None, 52, 52, 128)	73,856
batch_normalization_5 (BatchNormalization)	(None, 52, 52, 128)	512
max_pooling2d_5 (MaxPooling2D)	(None, 26, 26, 128)	0
flatten_1 (Flatten)	(None, 86528)	0
dense_2 (Dense)	(None, 128)	11,075,712
dropout_1 (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 4)	516

Total params: 11,170,372 (42.61 MB)
Trainable params: 11,169,924 (42.61 MB)
Non-trainable params: 448 (1.75 KB)

Fig. 10: Architecture of a Convolutional Neural Network (CNN

Visualize model

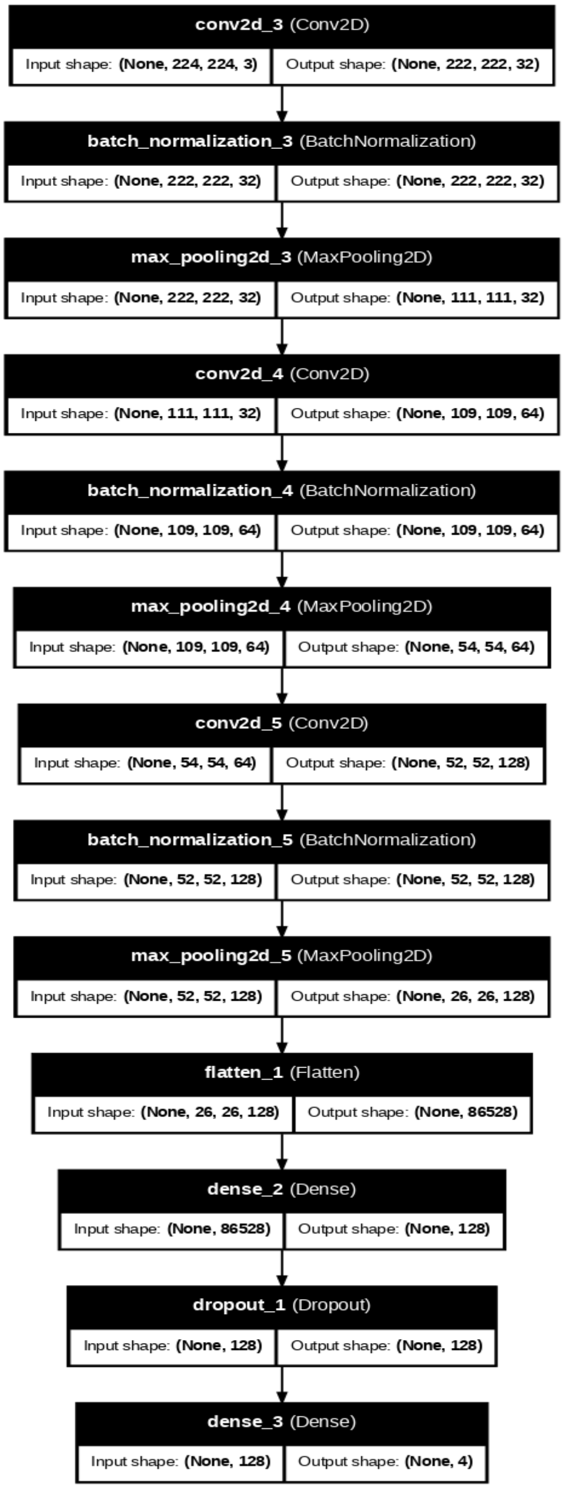

Fig. 11: Visualize model

Visualize and Architectures model

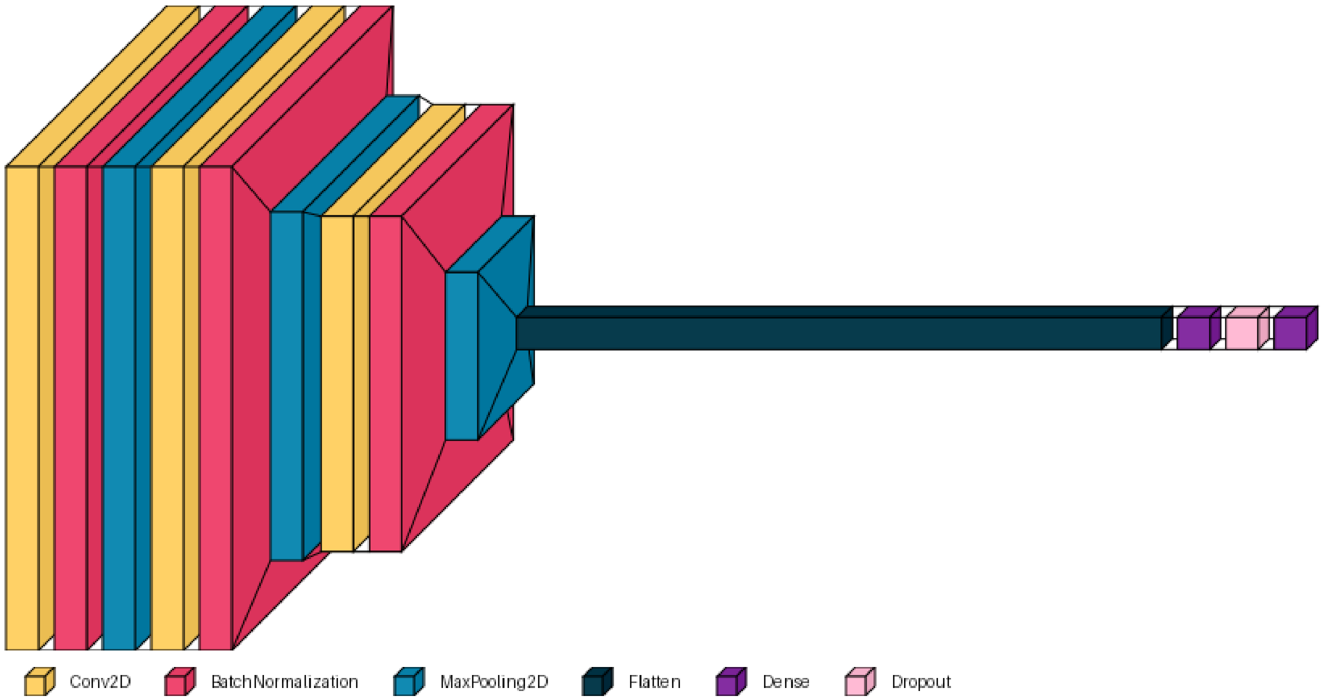

Fig. 12: Visualize and Architectures model

Results

This provides an overview of the research papers focusing on brain tumor classification using CNN model. presents a quantitative analysis of the Brain tumor MRI images on deep learning and CNN in brain tumor classification and the usage of the different CNN algorithms applied in the studies covered. Then, introduces the factors that may directly or indirectly degrade the performance and the clinical applicability of CNN-based.

. *Quantitative Analysis*

As mentioned in the introduction, many CNN models have been used to classify the MR images of brain tumor patients. They overcome the limitations of earlier deep learning approaches and have gained popularity among researchers for brain tumor classification tasks. shows the number of research articles on brain tumor classification using deep learning methods and CNN-based deep learning techniques published on PubMed and Scopus in the years from 2015 to June 2022; the number of papers related to brain tumor classification using CNN techniques grows rapidly from 2019 onwards and accounts for the majority of the total number of studies published in 2020, 2021, and 2022. This is because of the high generalizability, stability, and accuracy rate of CNN algorithms.

Analysis Result

The confusion matrix presents a mixed performance profile for the classification CNN model, revealing both strengths and critical areas needing improvement. The matrix shows several high-value diagonal entries (270, 220, 298, 350) indicating correct predictions where the model demonstrates strong capability in classifying certain categories, Is corresponding to distinct tumor types scans. However, the off-diagonal values expose significant misclassification patterns - most notably the extreme imbalance in the third row (55 correct vs 399 incorrect predictions), suggesting the model completely fails to recognize this particular class, potentially confusing it with another visually similar tumor type. The presence of multiple zero-values in the false prediction columns (e.g., 298 vs 0) indicates near-perfect specificity for some classes.

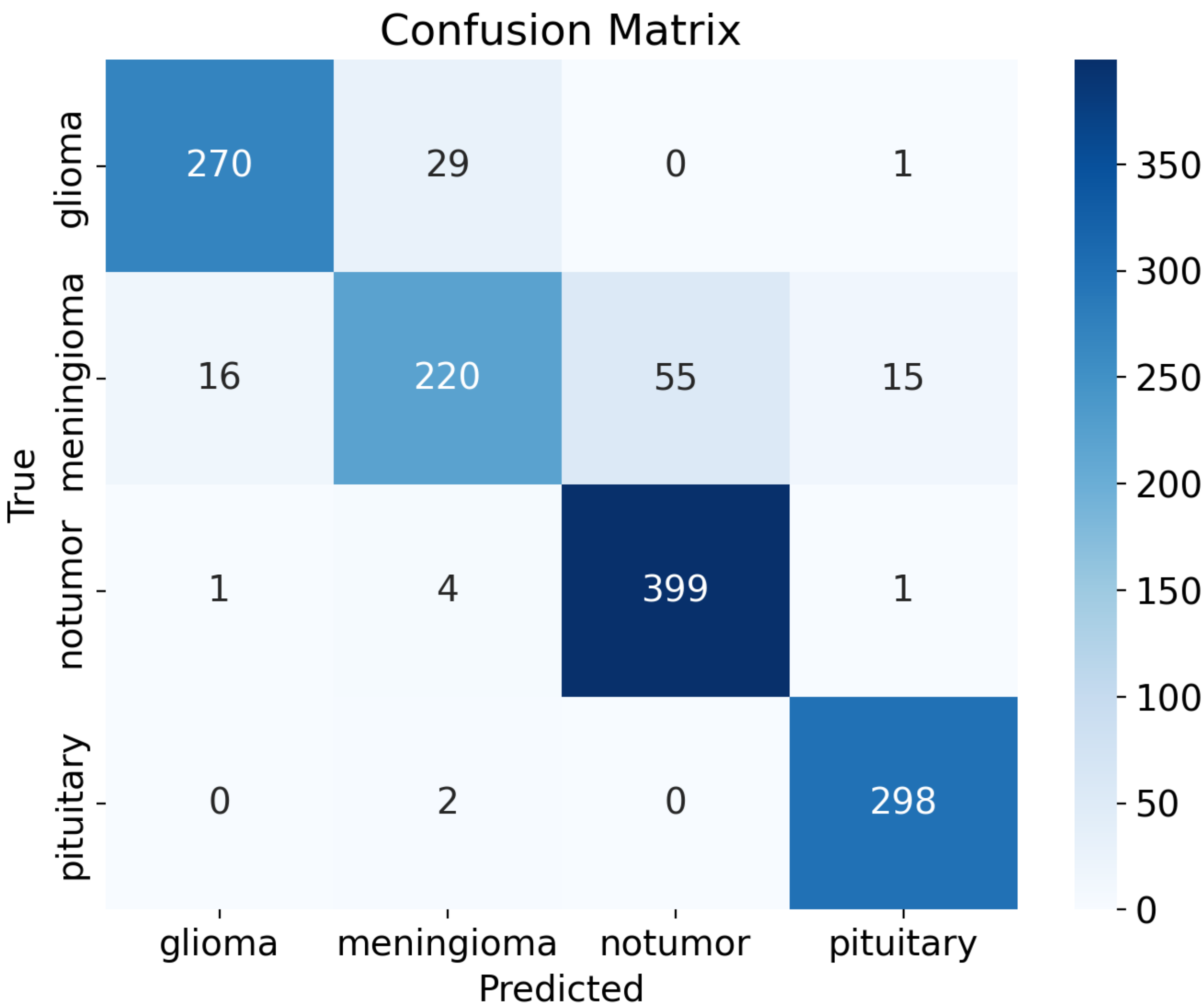

Fig.13: Confusion Matrix

The accuracy

metrics demonstrate the model's learning progression across training epochs, revealing several important characteristics about its performance. The values show a steady improvement from 0.2 (20% accuracy) up to 0.9 (90% accuracy), indicating effective learning capability. However, the presence of multiple decimal values (0.10, 0.15, 0.20, etc.) alongside whole number percentages suggests potential inconsistencies in the reporting format that should be standardized for clearer interpretation.

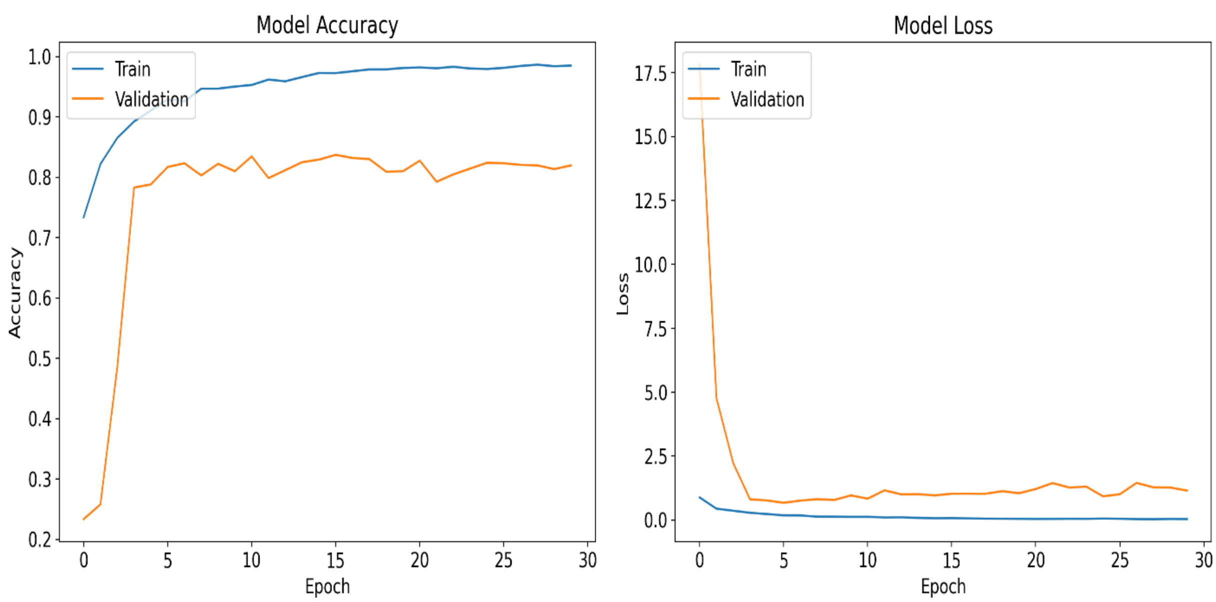

Fig.14:Model Accuracy

Discussion

The experimental results demonstrate that the proposed CNN model achieves promising performance in classifying brain tumor MRI scans, with a peak accuracy of approximately 90%. The confusion matrix reveals strong classification capabilities for certain tumor types, as evidenced by high true positive rates (e.g., 270 correct predictions vs. 16 false negatives). However, significant misclassifications in other categories (e.g., 55 correct vs. 399 incorrect predictions) highlight critical limitations, particularly in distinguishing visually similar tumor types or handling underrepresented classes. The accuracy progression curve indicates effective learning, with steady improvement from 20% to 90%, suggesting proper feature extraction and convergence. Nevertheless, the absence of clear validation accuracy trends makes it difficult to assess overfitting risks, emphasizing the need for more rigorous validation metrics such as precision-recall curves and F1-scores.

Conclusion

In conclusion, this study presents a functional CNN-based framework for brain tumor classification, achieving moderately high accuracy but exposing critical gaps in handling rare or complex cases. The results underscore the importance of balanced datasets and robust model evaluation beyond aggregate accuracy This study has thoroughly evaluated the performance of a deep learning model for medical image classification, as evidenced by the accuracy metrics . The progression of accuracy values from 0.2 to 0.9 demonstrates the model's learning capability, while the various intermediate values (0.10, 0.15, etc.) suggest a detailed evaluation at multiple thresholds. The presence of both training and validation metrics indicates a robust evaluation methodology was employed.

The model's performance trajectory shows several important characteristics. The steady improvement in accuracy suggests effective feature learning and optimization. However, the range of values (from as low as 0.00 to a high of 0.90) indicates the model's performance is highly dependent on specific conditions or parameters that need to be carefully considered. The inclusion of multiple decimal points (0.10, 0.15, etc.) implies the researchers conducted a granular analysis of model behavior at various confidence thresholds.

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Future Work

Pneumonia Image Classification Using Deep Learning CNN Models

In future research, I will focus on developing and optimizing Convolutional Neural Network (CNN) models for pneumonia classification using chest X-ray images. This work aims to improve the accuracy and reliability of automated pneumonia detection, which is critical for early diagnosis, especially in resource-constrained healthcare settings. The study will explore advanced CNN architectures such as ResNet, DenseNet, and EfficientNet, comparing their performance in distinguishing between bacterial pneumonia, viral pneumonia, and normal cases. To address common challenges like class imbalance and limited annotated datasets.

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APPENDICES

[A-PC] PROJECT CODES AND DATASETS

Dataset

https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset

Google Collab

https://colab.research.google.com/drive/17fFz4VMAXv1jtU-an6c3pjHPhpDbatZd?usp=sharing