MRI BASED BRAIN TUMOR CLASSIFICATION AND DETECTION THROUGH MULTI-MODAL DEEP LEARNING TECHNIQUES

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MRI Based Brain Tumor Classification and Detection through Multi-Modal Deep Learning Techniques

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Candidate of **Master of Science in Software Engineering (MSSE)** at the National University of Modern Languages do hereby declare that the thesis **MRI Based Brain Tumor Classification and Detection Through Multi-Modal Deep Learning Techniques** submitted by me in partial fulfillment of MSSE degree, is my original work, and has not been submitted or published earlier. I also solemnly declare that it shall not, in future, be submitted by me for obtaining any other degree from this or any other university or institution. I also understand that if evidence of plagiarism is found in my thesis/dissertation at any stage, even after the award of a degree, the work may be cancelled and the degree revoked.

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ABSTRACT

Title: MRI Based Brain Tumor Classification and Detection Through Multi-Modal Deep Learning Techniques

Machine learning and deep leaning methods have substantially advanced the efficacy of disease diagnosis in healthcare setups, by facilitating precise and early prognosis of disease, enabling timely intervention and resource optimization. One of the key field where it is stated beneficial is brain tumor diagnosis, a most serious disease which can adversely impact the people of any age group. Despite of significant advancements in the field of deep learning in visual data processing there are still challenges. The research highlighted important challenges in brain tumor scrutiny; comprising morphological uncertainty, tumor heterogeneity, class imbalance, data scarcity, and model accuracy. Besides these challenges the processing of various medical imaging modalities; i.e the data which is obtained from different medical devices like MRI, CT, and PET have inconsistent features, the accuracy results are variant and inadequate. By considering these factors, the research is based on development of two deep learning models; the LSTM model and hybrid 2D UNET + LSTM model to accurately identify and classify four types of brain tumor. Firstly, MRI images are preprocessed using N4ITK bias field correction to eliminate intensity inhomogeneties and to boost their qualities. Then the proposed Hybrid model combine the 2D UNET and LSTM networks, with 2D UNET having four convolutional blocks with variable number of 3x3 sized filters. The networks and layers arrangements are chosen after extensive experimentation. Model performance was accessed using various key metrics including precision, recall, F1 score and specificity. The results demonstrate a significant accuracy of 99.12% of hybrid 2D U-Net + LSTM which outperforms the standalone LSTM model. Additionally, comparative analysis with existing research is performed which notices the better outcomes of the proposed models. Therefore, the research helps in advancing tumor classification accuracy and reliability in medical research.

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LIST OF ABBREVIATIONS

BTS	-	Brain Tumor Segmentation
CAD	-	Computer-Aided Diagnosis
CNN	-	Convolutional Neural Network
DL	-	Deep Learning
DTI	-	Diffusion Tensor Imaging
GAN	-	Generative Adversarial Network
KNN	-	K-nearest Neighbor
LR	-	Logistic Regression
LSTM	-	Long Short- Term Memory
MLP	-	Multilayer Perceptron
MRS	-	Magnetic Resonance Spectroscopy
NB	-	Native Bayes
PI	-	Perfusion Imaging
RF	-	Random Forest
SVM	-	Support Vector Machine
WHO	-	World Health Organization

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DEDICATION

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As this thesis takes its place on the academic stage, I dedicate it to the cherished individuals who have played pivotal roles in my life. May this dedication stand as a humble acknowledgment of the profound impact each of you has had in shaping my academic pursuits. Additionally, I extend appreciation to the broader academic community, whose collective wisdom and resources have been instrumental in the development and completion of this research.

CHAPTER 1

INTRODUCTION

1.1 Overview

The primary aim of this research is to develop a MRI based automated brain tumor detection and type classification model using deep neural networks. Thus, helping in improving the accuracy significantly through automated system.

In particular, the objectives are as following: Use of UNET architecture for detailed feature extraction from MRI medical imaging. LSTM model is mainly used for sequential data processing used for classification of brain cancer into four main classes (i.e pituitary gland, glioma, meningioma , and no tumor).

1.2 Motivation

In the human anatomy, the brain serves as the control center for the neurological system. Brain cancer is a serious disease which can adversely impact the people of any age group, for example glioma, meningioma, and pituitary [4]. Early brain tumor detection and prompt treatment greatly enhances the chances of patient survival [4]. As per WHO guidelines, a brain tumors are graded from I to V . Grade I and II are benign (slow-growing tumor) and referred to as low grade, while grade III, IV, V are malignant (aggressive) and referred to as high grade tumor[1]. Since neuro biopsies typically requires surgeries rather than normal treatment. Therefore, importance of finding non-invasive alternatives for accurate diagnosis is crucial [12]. MRI is just one of many imaging modalities that doctors employ to determine whether or not a tumor is present. MRI is a safe, highly significant way to learn about the location, size, and form of brain tumors using contrast imaging [13].

Now a days, deep machine learning a subset of machine learning uses different methods which are frequently in use for efficiently processing large amount of complex data, for accurate identification and classification of medical imaging patterns [12]. Many different DL models including 2D, 3D and hybrid models have been developed by researchers using MRI images as datasets for presenting an improved model for segmentation and identification of brain tumors automatically. Various brain tumor segmentation approaches have come into consideration which can be categorized as manual, semi-automatic, and fully automatic. Manual segmentation techniques are time consuming and difficult to manage as it highly requires radiologists involvement and knowledge [14]. Automatic segmentation methods offer less time and produce more accurate results, they are categorized into two categories: supervised and unsupervised detection methods.

The most often used architecture for biomedical image segmentation task is UNET architecture which shows the exceptional performance when combining with other models to achieve desired results. The UNET model is built on the principle of fully convolution network to extract multi-state features [17]. It uses different training layers for feature extraction and classification tasks; based on the performance feedback the number of these training layers can be adjusted. However, existing image segmentation and classification methods are still facing various challenges. Furthermore, lesion localization and tumor segmentation are vital for medical imaging judgments.

This challenging and intricate endeavor requires precise algorithm and robust network architecture to accomplish. In consideration of these aspects, the UNET architecture in fusion with LSTM is implemented in this research to develop a hybrid deep neural model for multi-class classification in brain scans. MRI brain tumor images are employed as dateset due to their non-ionizing radiation nature and superior resolution.

1.3 Applications of Deep Learning Models

Deep learning models are widely used in various fields due to their powerful segmentation and classification capabilities. Some of the key applications of these models are as follow:

i. UNET is a sophisticated deep learning model which is widely used in various fields for diagnosis of different diseases. It is mostly used for segmentation purposes in biological and medical imaging applications due to its powerful ability to capture fine details. In medical imaging applications, it is widely used for tasks like lesion recognition, brain tumor segmentation, and organ detection.Additionally, it is also used in segmentation of heart, lungs, liver, lymph nodes, esophagus from medical images, thus assist medical professionals in prognosis of disease and treatment planning by automatically analyzing images by capturing their fine details[1].

ii. In biological applications, UNET has been effectively utilized in analyzing marine sponge behavior like changes in its size and activity due to environmental variations by carrying out semantic segmentation of high resolution time series images. Thus it has ability to support ecological monitoring [2].

iii. In remote sensing application UNET is utilized for automatic change detection in satellite images obtained at various time epochs, by analyzing these images and monitoring human actions and their interaction with environmental changes[3].

iv. In the field of meteorology, UNET is used for weather forecasting and precipitation now casting. It analyzes the short-term patterns in precipitation maps and cloud coverage images to make weather predictions by leveraging capabilities of its convolution blocks and attention mechanism [4].

v. Another application of UNET is in the field of image super resolution, as it takes deteriorated low resolution image in the input and reconstruct them to high resolution image by identifying mapping among them.It is therefore also applicable for improving projector resolution and handling degradation of complex images while improving the quality and clarity of image with diminished reconstruction stumbles [5].

vi. LSTM is widely used in natural language processing (NLP) which is used to develop AI emotion recognition software. These software in medical field captures patient emotions like anger, fear, happiness, disgust, sadness, and neutral emotions at specified time intervals. Like in hospital patient communication's contextual information and temporal dependencies can be accurately capture, thus help in emotion detection for physician better response suggestions. Thus it can help in improving the communication between patient and service provider [6].

vii. LSTM in fusion with Multi-Layer Perceptron (MLP) is used to develop the speech recognition applications that automatically converts speech to text. In online language learning platform's applications such as English language learning software uses LSTM for handling sequential voice data, they process and recognize the spoken language and convert it to text. This improves the applicability of online platform through its effective learning mechanism[7].

viii. In block chain security enhancement, fraud detection, and anomaly detection LSTM played pivotal role. In block chain based transaction LSTM auto-encoders can recognize suspicious patterns and fraudulent activities which reduces the security threats. It helps in making blockchain models more secure by learning transaction behavior over time [8].

1.4 Problem Background

Brain tumor identification and classification from MRI data presents various challenges. The primary challenges is limited labeled dataset and class imbalance which causes stability of training convergence issue and poor accuracy of models[12]. In an effort to fix this, the study utilize data augmentation and startified sampling methods to artificially expand the dateset and to balance class distributions.

Additionally, MRI data exhibits varying intensities, tumor locations and sizes, making it more complicated to categorize tumor type and detect their boundaries[28]. To reduce this effect of intensity in-homogeneity; N4ITK bias field correction preprocessing is applied to make consistent intensity level all across the image. Most of traditional CNN based classifiers process MRI data as static input, and discards contextual relationships like the appearance of tumor across different slices, how tumor structure varies in time or space and dependencies between adjacent regions or pixels.This research designed a hybrid model that combines the UNET architecture for feature extraction and LSTM for temporal data recognition thereby aims to improve the detection and classification accuracy of brain tumor.

1.5 Problem Statement

Brain tumor detection models have faced several sound challenges including variable shapes and sizes, intensity in homogeneity, non uniform illuminations in medical imaging, class imbalance, accuracy and stability of convergence issues. Existing models frequently consider MRI scans as static inputs while discarding contextual relationship between features despite of their encouraging results. This research proposed an improved hybrid deep learning model which integrates LSTM network to capture inter-feature relationships for better classification with U-Net for efficient feature extraction. The model seeks to improve detection accuracy and classification across a variety of complicated MRI data by integrating various methods.

1.6 Research Questions

The research questions are as follows:

1. *RQ1:* How does the proposed hybrid UNET+LSTM model's performance compared with the existing brain tumor classification model?
2. *RQ2:* How does the proposed model handle the issue of class imbalance and stability of training convergence in brain tumor detection and classification systems?

1.7 Research Objectives

The following research objectives will be pursued to achieve the research aim:

1. *Obj 1:* To develop an automated hybrid 2D UNET+LSTM brain tumor classification and detection model.
2. *Obj 2:* To analyze how the proposed model mitigates class imbalance and stability of training convergence for improved detection and classification of tumor from MRI images.

1.8 Aim of Research

The research aims to make significant contributions to the field of medical imaging and brain tumor diagnosis by developing an improved deep learning model that integrates the strengths of two deep neural networks long short-term memory (LSTM) and 2D U-NET architecture.

1.9 Scope of Research Work

The scope of research is to build an improved automated model for the detection and classification of brain tumors using advance deep learning techniques. The main objective is to develop an enhanced system capable of accurately identifying tumors in MRI imaging data, and classifying them into different types based on their characteristics. The proposed model utilizes UNET architecture for segmentation and Long Short-Term Memory (LSTM) for handling temporal dependencies in MRI images. Ultimately, this study objective is to contribute to medical imaging research by providing a reliable tool for automated brain tumor recognition and type classification, aimed at increasing diagnostic accuracy and more favorable patient results.

1.10 Thesis Structure

Chapter 1 introduces the motivation and aim of research focused on developing an automated tumor recognition and type classification model. It outlines the scope of research, problem statement, applications of deep learning models. A comprehensive literature analysis is given in chapter 2. It examines deep learning based brain tumor classification methods and their constraint, various traditional machine learning, CNN based and variant models. The comparison of various approaches and research gaps are identified in this chapter.Chapter 3 combines important ideas and techniques into a logical framework that directs the investigation. In-depth details regarding the datasets used, preprocessing methods, LSTM and U-Net model designs and development,tools used to attain the desired results are written in this chapter.Chapter 4 provides a comprehensive review of the study's findings, outlining key findings and outcomes through comparative analysis. Finally, Chapter 5 concludes the thesis by summarizing the main conclusions, considering the study methodology, and providing suggestions for further research.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

Several studies have been conducted on automated brain tumor classification and detection methods. Different deep learning models also including hybrid approaches have been used for detection and classification purpose. This study focused mainly on papers that contribute to the development of model for MRI based brain tumor detection and classification. Then several problems associated with implementation of models have been identified and pertaining issues have been discussed. Some of the existing models showed exceptional performance in their hybrid approaches, while others did not.

2.2 Addressing Deep Learning Approaches for Brain Tumor Classification and Existing Constraints

The deep learning algorithms for brain tumor classification encounters several problems in implementation and deployment, that require meticulous analysis. These problems are discussed below.

2.2.1 Data Scarcity, Class Imbalance and Low Quality Medical Imaging

The data act as a fuel in training a deep learning model as it impact model's performance like prediction accuracy, model generalization and robustness [16]. Most of the well structured architectures (like CNN, UNET, and LSTM) even need struggle without appropriate size and quality of data to attain desirable results. Large and diverse data set comprising various tumor classes, shapes, sizes and locality enables the model to improve its learning and generalization capabilities. These poor quality and size of data leads the model to issues like overfitting (in-case model shows good results on training set but fails when applied to novel data) and underfitting (where model can not learn enough required patterns). Additionally imbalanced dataset causes model bias issue and inconsistencies that needs to overcome for making AI based approaches applicable in real world.

2.2.2 Explainability and Interpretability of Model

Due to complex nature of deep neural network models in making predictions, these models are known as black box paradigm. It is crucial in medical field safety to comprehend and justify the model predictions. Healthcare professionals need demands interpretable and explainable model for making decisions. However, these AI based brain tumor classification methods can be more generally recognized by increasing model interpretability and explainability [16].

2.2.3 Model Robustness and Generalization Ability

Another challenge in deep learning models is that they should generalize seamlessly when evaluated on new, unseen data. Generalization is the ability of model to retain effectively when tested on unseen data from various sources, while robustness signifies how well a model can make consistent predictive performance subject to different conditions [16]. In medical imaging like MRI images can have various contrast level, resolution, noise factor, and demographics (images of different age group, gender and genetics). Additionally different manufacturer's equipment (like Siemens, Philips, GE ect) generate images with distinctive characteristics. Therefore a model trained on specific dataset might find difficult to correct classification on different demographic data, thus resulting biased predictions.Without model generalization and robustness, even a highly efficient model could fail in practical environment, having an avenue of safety risk and misdiagnosis.

2.2.4 Clinical Validation and Regulatory Standard Compliance

Clinical validation and regulatory standard compliance refers to testing of neural network models to ensure their efficacy, accuracy, and compliance with healthcare regulations before bringing them into practice [16]. This help to identify model performance and reduce the errors like false positive (incorrectly finding tumor in a healthy brain) or false negative (not highlighting a tumor even if it is present). The key challenges for carrying out validation activities are given below:

1. Black box nature of AI models
2. Time taking and resource intensive
3. Model biasing and fairness problems

2.3 Segmentation Methods for MRI Images and Pertaining Challenges

2.3.1 Uncertainty of Location in Brain Tumor Segmentation

It is not an easy task for radiologists and medical professional to segment the exact location of tumor boundaries because of the Variation in shape, size, image quality and anatomical location of tumor. some tumors are large and other may be small in size also it may appear in different areas of brain such as brainstem, cerebral hemispheres, or cerebellum[18]. A poor segmentation can lead to mistakes in treatment planning and issues of over-segment (pinpoint normal tissue) and under-segment (neglect tumor region).

2.3.2 Morphological Uncertainty in Segmentation of Brain Tumor

Morphological uncertainty refer to as the inability of model to pinpoint tumor boundaries for segmentation of brain tumor. Several factors causing this difficulty includes diffused glioma structure, in which Malignant High-Grade Gliomas (HGG) and benign Low-Grade Gliomas (LGG) diffused with connecting tissues, and makes it difficult to identify tumor boundaries. The tumor is surrounded by an outer layer called edema tissues, edema tissues resembles with tumor tissues, causing the issues of over-segmentation(specifying edema as tumor) and under-segmentation (missing tumor area) [18]. For brain tumor segmentation, machine learning models learned on uncertain tumor boundaries patterns can produce inaccurate predictions, thus poorly affecting the clinical confidence on automated segmentation techniques.

2.3.3 Annotation Bias in Segmentation of Brain Tumor

Annotation bias is a problem that arise when manual segmentation is being carried out by medical professional for segmentation of brain tumor from brain images. As it is a difficult task and require high expertise, otherwise it leads poor impact on training , testing and generalization capabilities of model. Since the radiologist may have distinct level of expertise and experience causing different interpretations. The way radiologists highlight the tumor locations can be unintentionally influenced by personal preferences, past experiences, and expectations. Additionally, In order to avoid annotation inconsistencies, some radiologists may use conservative approach and just label the core tumor, while others may also mark edema and infiltrative zones[18].

2.4 Existing Literature

In recent studies, deep neural network algorithm for brain tumor classification and detection have been explored extensively. Different deep machine learning principles such as CNN, LSTM and hybrid models have been used to process Neuroimaging data for automated brain tumor recognition and type classification which achieved high accuracies. Following are some of the relevant studies in the literature.

2.4.1 Classical Machine Learning Models

Before the advance neural network modeling, traditional machine learning based algorithms like Decision Trees, Random Forest and Support Vector Machines (SVM) were frequently used for feature analysis and data labeling. Some of the relevant studies of this approach includes:

For multi class classification of brain tumor Muhammad Imran Sharif (2021) developed an automated deep learning model. For feature engineering a well trained Densenet201 framework is used. Additionally, other features selection method like entropy-Kurtosis were employed. Finally, for multi-class categorization, a SVM (Support Vector Machine) classifier is deployed. The whole methodology is accessed using BRATS2018 and BRATS2019 databases and obtained an average accuracy of 95%. But it faces a limitation of fusion process which increases the computational complexity and time, while secondly eliminating some important features by model limits in applicability and usage in practical environments [37].

Azeez and Abdulazeez (2025) explored various scientific databases such as PubMed, Springer,IEEE Xplore, ACM Online Repository, ScienceDirect, and Google Scholar to provide a comprehensive summary of current brain tumor classification methods, while focusing on other stages of preprocessing, feature extraction and classification. Two noticeable architectures VGG and ResNet have been discussed. The VGG network uses multiple Convolution layers with a 3x3 filter, followed by max pooling layers. It is more applicable to get finer details of input images. While ResNet uses residual blocks that solves the vanishing gradient issue and helps in better partitioning and type classification tasks. The study compares the performance of classical machine data-driven learning techniques like SVM, Decision Trees, and Random Forests with complex neural networks specifically convolutional neural networks (CNN) and residual networks (ResNet) and noticed that DL approaches yield better results as compared to ML methods. The future research should focus on employing more advance preprocessing operations like gamma adjustments, robust data augmentation, window setting optimization. Additionally, focus should be placed on model improving model interpretability using Local Interpretable Model-Agnostic Explanations method and its clinical validation. By integrating multi modalities like CT, PET and MRI and extending focus on other brain diseases detection could significantly help in enhancing the accuracy, reliability and applicability of these models [38].

Fasihi and Mikhael (2021) proposed a novel classifier by integrating the hand crafted features and LSTM classifier, this approach elevated the classification accuracy even with weak supervised data. LSTM is a special type of RNN used for handling long term dependencies in sequential data and to address to the vanishing gradient and exploding gradient problem of RNN. LSTM introduced a memory unit called cell/memory unit, this unit keep on updating in each time zone. Single unit makes decision by considering current input, previous output and previous memory, the unit generates an output and alter its memory, as illustrated in Figure 2.1 [9].

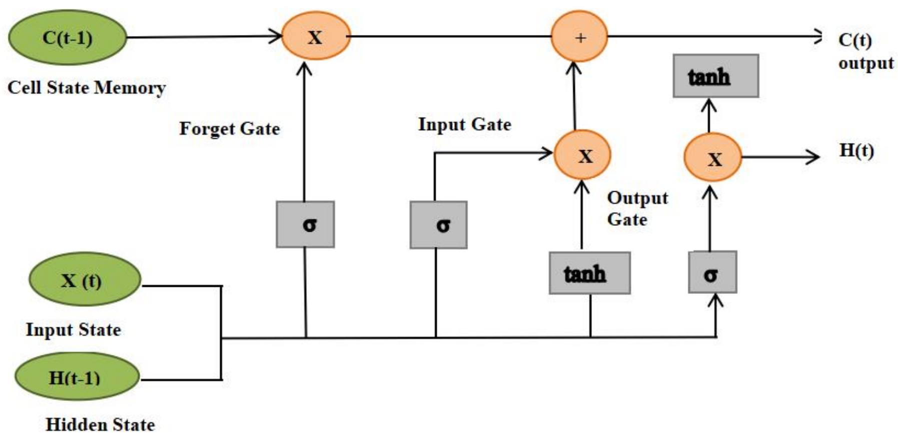

Figure 2.1: Architecture of LSTM

Their model extracts handcrafted features wavelet, DCT, and Haralick texture attributes from input imaging data and then employ LSTM classifier to categorize the tumor grade. DWT (Discrete Wavelet Transform) is applied to detect the region of interest by keeping time and frequency information from the images and LSTM classifier is used to process sequence of images data.The algorithm preprocess MRI images and resized them into 256x256 resolution, normalize to [0,1] and apply k-mean clustering to segment the tumor area. The features extracted are then serve as input to LSTM for tumor grade classification. The recommended model is applicable to several medical images even when all images have missing labels while achieving an higher accuracy as compared to other networks [39].

For brain tumor detection Saba & Mohamed and El-Affendi (2020) presented a novel approach that merges handmade features with deep learning features. Firstly the image segmentation is carried out using grab cut algorithm and integrated VGG-19 with Local Binary Patterns Descriptors (LBP) and Gradient-based histogram (HOG). Finally, for classification of tumor into healthy brain and glioma tumor several classifiers were used. In BRATS 2015, BRATS 2015, and BRATS 2017, the dice similarity index (DSI) test scores are 0.99, 1.00, and 0.99, respectively. The significant shortcoming of their work is its limitation to distinguish only between healthy brain and glioma tumor images [31].

Table 2.1: Summary of discussed literature related to traditional deep learning models

Ref	Purpose	Classifier/ Dataset	Limitations/ Future work	Results
[21], 2024	Developed ViT model named RanMerFormer for brain tumor classification	RanMerformer Model with token merging. Kaggle & Figshare dataset	ViT models require high computational cost than CNN, worst performance for meningioma classification	ACC of 99% for both dataset
[12], 2023	To classify brain tumor into four types	2D CNN and auto encoder decoder, MRI images dataset	Limited availability of labeled data, class imbalance, incorporating data augmentation, need of robust neural network in future work.	2D-CNN had 96.47% ACC, convolutionl auto encoder network 95.63%, MLP 28 %, & KNN 86%
[10], 2023	Review previous work to find common process for designing a deep learning	Data Augmentation, Model development, Pre & Post processing	Model overfitting, vanishing gradient &limited dataset issues. Transfer Learning, data augmentation implication as future work.	Binary Classification i.e tumor or no tumor
[9], 2022	Understand most advanced & recent deep	Literature Review, Deep generative networks	Overfitting, class imbalance and dealing with	deep learning , interpret-ability examination

	learning BTS & classification models & studying their benefits & limitations.	discussed	fluctuation Integration of various modalities of MRI like MRS, DTI and PI is recommended.	
[19], 2019	Provide a CNN and six ML classifier's approach for tumor localization.	CNN, Six ML Classifiers (i.e SVM, KNN,MLP, LR,NB,RF) Kaggle dataset	Focus on other tumor types, Incorporate large dataset and 3D MRI images for further improving model accuracy	92.98 % ACC with 70 : 30 split ratio, & ACC of 97.87% with 80:20 splitting ratio

2.4.2 CNN Based Deep Learning Classifiers Approaches

Most of the researchers have employed deep CNN models for data feature extraction and categorization from magnetic imaging data. CNN models are well suited for image processing tasks as they are highly effective for detecting spatial dependencies and hierarchical patterns in images. The general architecture of CNN model is depicted in Figure 2.2. Some of the CNN network based classifiers relevant studies are discussed below.

A novel approach named "SETL_BMRI" proposed by Natha (2024) for tumor localization and classification in brain scans. The framework was developed using AlexNet and VGG19 pre-tained models. Firstly a multilayered CNN model to find features and then afterward data augmentation is applied for the retrieval of more critical features. The VGG19 uses nineteen convolution operations and three fully connected layers for classifying the MRI images into three different categories.The dataset acquired in the research is publicly available over the internet comprises of three kinds brain cancers. The framework compares with other deep learning networks like ResNet50, DenseNet20, AlexNeta and VGG19. Detection and differentiation of brain tumor types using SETL_BMRI model was more precise and correct ,with precision, recall, and F1-measure of 98.75%, 98.6%, and 98.75%, correspondingly. Further studies are needed to get the most precise estimation of affected brain regions by discerning them from non impacted regions, a number of techniques for image segmentation will be used [41].

Nourish et al., 2023 developed a class categoarization system relies on convolutional neural network (CNN) to categorize normal and brain tumor images. The proposed model was evaluated using medical imaging MRI dataset of 253 images from Kaggle website. Firstly data augmentation is executed to enhance the dataset, secondly image preprocessing applied to crop the unwanted areas and getting justifying images and in the last phase the CNN model comprising of many convolutional and pooling layers is employed. Evaluation of proposed model is conducted through calculating accuracy, sensitivity and specificity metrics, and showed an precesion of 94.51%, a sensitivity of 96.31% and a specificity of 92.51% . More dataset needs to be incorporated to investigate type classification of other tumor types in future work[26].

Majib and Rahman 2021 proposed a novel transfer learning based approach named VGG-SCNet, while the author also analyzed and compared 16 different transfer based learning models to trace the best one for brain tumor classification. Manual prediction methods are time consuming and highly dependent upon the radiologist's empirical experience. The proposed VGG-SCNet (VGG Stacked Classifier Network) achieved precision, recall, and F1 scores of 99.2%, 99.1%, and 99.2%, respectively[28].

Manual methods for classifying and detecting brain tumors are time consuming and leads to inaccuracies. In order to automate the process the author (2024) develop three CNN based models for various classification tasks. CNN model is commonly used DL model having different layers such as input layer, convolutional layers and pooling layers for feature extraction whereas fully connected and classification layers are used for classification purposes.The first model developed for binary classification of tumor depicts an accuracy of 99.53%. With an accuracy of 93.81%, the second model efficiently classify the tumor into five classes: glioma, meningioma, pituatary, metastatic and no tumor. It has 25 weighted layers, the ouput layer predict the type of tumor by receiving five dimensional feature vector as input produced by fully connected layer of model. Furthermore, the third model categorizes the brain tumor into different levels with 98.56% precision rate. Grid search is used to automatically fine tune the hyperparameters. The study uses four different datasets i.e Figshare, REMBRANDT, TCGA-LGG, TCIA and then split-up them for model classification and detection tasks. The proposed CNN model work well in comparison with other DL models like GoogleNet,AlexNet, DenseNet121,and ResNet101[42].

Early diagnosis of brain tumor is crucial as it is non-invasive and patient does not go under biopsy. Manual techniques hampered accurate detection due to intrinsic nature of brain tumor and variable sizes, shape and location. Due to this pressing need for automated system naeem and javaid (2023) suggested new model named TumorDetNet. The main motivation is to develop framework that can detect and classify brain tumor with high accuracy without performing prior tumor segmentation, while presenting MobileNetv2 architecture. All the images are resized to 124x124 resolution and then fed as input to model input layer which then down samples the image to decrease the model's computational complexity. MobileNetv2 is a light weight deep leaning architecture that uses the depth wise feature extraction layers which are computationally less costly. The framework uses these depthwise convoltional layers followed by Leaky RELU and RELU activation function for learning more complex attributes from source image. The output feature vector fed into final fully connected feedforward layer that maps the feature vector into four main classes, the FC layer then uses the softmax activation function in the output for multiclass classification of brain tumor. Overall 129 layers for extracting features and five layers for classification purpose uses. The model shows a remarkable accuracy of 99.83%. However, the study provides valuable insights of memory usage, system complexity, and computing time that are limited and may require further exploration for wider applicability [43].

Aamir and Rahman (2022), introduced a novel method detecting brain tumor using MRI scans. The model based on transfer learning,partial least squares (PLS), agglomerative clustering algorithm obtained an accuracy of 98.95% in brain tumor type classification, outperforming existing traditional classifiers. The study detailed the preprocessing using illumination boost approach and nonlinear stretching, feature extraction, image proposals generation and refinement, their alignments and classification, and comparison with other existing approaches, high lightening the performance and effectiveness of proposed model in brain tumor classification [44]. Saxena and Chauhan (2025) discussed the deep learning approaches like CNN used for brain tumor classification and segmentation. These advanced approaches help in automating the processes thus by reducing the workload while increasing the accuracy. The study introduced a new model, which uses a dataset comprises of four classes and then a five layer CNN is used for tumor detection. The proposed model shows an accuracy rate of 97.87%. Although the presented model deliver promising classification outcomes but still faces some challenges. One of the key challenge is requiring large radiologists annotated-instances, crucial for model accuracy and generalization capabilities.

Further investigations are needed to study methods like few-shot, zero-shot, and advance reinforcement learning to mitigate reliance need on large dataset [45].

In another study, Oinar and Yildirim (2020) implemented another model in which REsNet-50 served as base architecture. This model was modified by eliminating its last five layers and adding eight new layers in its replacement. Their work has a limitation of lacking the ability to distinguish between specific tumor type as it solely targets on binary classification[46].Noreen implemented Inception-v3 and DenseNet201 architecture with softmax classifier to implement two distinct multi-level models. It uses multiple modules for feature engineering, these attributes then concatenated and then provided to activation softmax for classification task in these per-trained models [47].

The DL models poses many significant challenges of including limited data, model's high computational cost, and low accuracy rate. A light weight CNN based model to overcome these obstacles and which significantly reduces the complexity over existing models was suggested by Hammad (2023). The study uses two datasets; the first dataset contains Enhanced T1-weighted MRI images and the second dataset consist of MRI images with tumor and no tumor.All the images are in .jpeg format which then pre-processed using skull stripping and intensity normalization techniques. All the images are annotated by expert radiologists manually for identification of tumor region. There are less number of convolution blocks used in the model, while it outperforms by scoring an accuracy of 99.48% in binary labeling and 96.86% in multi class labeling. As future work, further investigations are required to address the obstacles of implementation of automated DL models in IoMT setup, also avoiding biases in training dataset by incorporating other robust methods like cross validation for ensuring model generalization. Likewise training on diverse data set including various MRI modalities can furthur help in avoiding model overfitting and misdiagnosis issues [48].

Islam and Azam (2024) designed a brain tumor classification model by using three merged datasets. The images are converted to gray scale to ensure consistency in data. By analyzing the efficiency of 13 layered 2DCNN, LSTM and another nine layered 2DCNN the best accuracy is 98.47%. The author separately trained and accessed the performance of each network and noticed that 2D CNN LSMT outperforms as compared to others. The 2DCNN

LSMT model uses a series of feature extraction layers followed by max pooling operation layer and drop out layer in order to diminish the image spatial dimensions and to avoid overfitting issue. To make a hybrid model using ensemble learning all the models are combined and compiled for evaluating other key hyperparameters.In order to improve the effectiveness and usefulness of proposed strategy , the author recommended to investigate more techniques for identifying region of interest in tumors [49].

In another research work, Devanathan and Kamarasan (2022) three models MOAOA-FDL model, MOAOA-FDL, and AOA with Shannon entropy are used for brain tumor classification, image preprocessing and image segmenation purposes. Primarily the images are preprocessed and then Shannon's entropy is applied to segment the image and find the area of interest, then image caharacteristics are extracted using entropy preocess. The extracted features fed into AOA-LSTM model that perform classification. Among the three approches MOAOA-FDL outperform with an accuracy of 98.95% when evaluated using kaggle and figshare datasets. The proposed MOAOA-FDL technique can be used with other instance segmentation methods. Further research may also focus on testing the model's performance on wide and real-time datasets in order to increase its applicability and effectiveness in practical environment [50]. Abbas and Ali (2024) suggested two models named CNN-LSTM and CNN-BiLSTM models. Initially image segmentation is being carried out which segments the image into foreground and background and separates the affected area containing tumor. These segmented images are then serve as input to the classification models (CNN-LSTM) and (CNN-BiLSTM) for extracting features. Both these models uses a pretrained Resnet50 for extracting complex features.The Resnet uses 50 layers and it extracts 1000 features for a single input image. Then these features fed into classifier for further brain tumor classification. The findings of the study showed that the model significantly improved the classification results, with achieving an accuracy of 97.86 for LSTM and 99.77% for BiLSTM with less training time of 58 and 91 seconds of two models. However the significant limitation of the study is small dataset size used for experimentation, which effects the generalization of findings therefore incorporating more diverse dataset is recommended [51].

In another study Amoury and Smili (2025) employed Particle Swarm Optimization (PSO) with CNN for tumor classification. This framework processes CNN hyper-parameters and training dataset like maximum allowed layers. Using PSO, it finds global best particle (gBest) by optimization the process of selecting layers without manual intervention. It is an iterative process containing six steps including particle fitness assessment, particle comparison, velocity calculation, particle updates, CNN encoding, and swarm initialization. In each cycle high performing layers are retrained for carrying out most valuable features. This performance-driven method automatically fine tune configuration factors like filters count and their dimensions, number of neurons, and total number of layers for achieving optimal configuration.The performance of CNN is noticed by analyzing confusion matrix and results shows that PSO-optimized CNN attained an accuracy of 99.19%. Future research can be conducted by testing on various dataset and other tumor types. Additionally, exploring more approaches that integrate PSO with other algorithms can further enhance performance, like using PSO algorithm with RRN or LSTM, will significantly help in improving its applicability beyond CNN architectures [52].

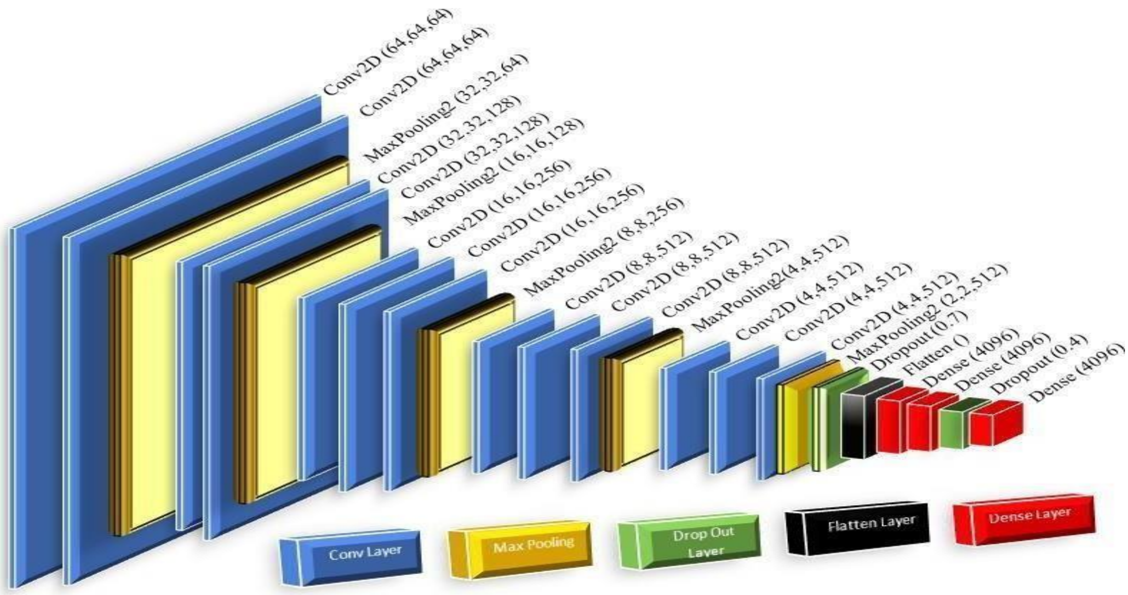

Figure 2.2: Convolutional neural network structure

Sohaib Asif (2023) in another study achieved an accuracy of 96.67% and 95.87% using two different datasets. The first dataset consist of three classes while the second dataset has four different classes. The framework uses five pretarined model for classification of brain tumors including Xception, DenseNet201, DenseNet121, ResNet152V2, and InceptionResNetV2. Additionally a softmax activation layer and deep neural block added in the final layer of this framework. But this method faces the limitation of unable to handle the varying situations [53]. Guder and Kaya (2025) modified CNN model which incorporates attention mechanisms leverages Particle Swarm Optimization (PSO) algorithm to pinpoint the optimal hyper-parameter values.The model trained by using a dataset consisting of four different classes obtained from kaggle. Their method achieved a highest accuracy of 99%. Attention mechanisms are used to highlight specific regions or features on the input feature map and are are classified as Channel Attention Module and Spatial Attention Module. In order to find the best model by integrating PSO three models ChannelNet, SpatialNet and CbamNet were developed. SpatialNet attained an accuracy of 99% on clean test dataset, while ChannelNet was reached on an accuracy of 97.78% on noisy dataset . The future work may incorporate the CNN with other handcrafted approaches for extracting features and promote feature selection and hyper-parameter by implementing meta-heuristic techniques. The efficiency and practicality of medical imaging models are supposed to be raised by these improvements [54].

In another study Dipu and Shohan (2021) presented two deep neural networks for brain tumor localization and classification in brain sacans.The object-detection technique You Only Look Once (YOLO) and FastAi library as their two techniques. The dataset is obtained from open source kaggle Brats-2018 comprises of 1992 MRI images. Their proposed model YOLOv5 has attained an accuracy of 85.95%, whereas the FastAi classification model scores 95.78% accuracy [55].

Table 2.2: Summary of discussed literature related to CNN based classifiers

Ref	Purpose	Classifier& Dataset	Limitations / Future work	Results
[24], 2023	Introduced hybrid model for automatic tumor recognition.	Hybrid model (KNN+GBC), 3D & 2D UNET RSNA-MICCAI dataset from Kaggle	Insufficient samples to train model, incorporate more data samples	64 % ACCU of 2DUNET, & 71% with 3D-UNet
[18], 2023	To provide overview of deep learning based federated learning techniques for image	Literature Review, BraTS challenge(2012 - 2021), ISLES	Uncertainty of location, morphological uncertainty issue,	cascaded networks, ensembling techniques utilize pre-trained

	segmentation and classification tasks.	2015,2016,2017, TCGA-GBM used in most of studies	low contrast, biased annotation, & class imbalance develop more complex protocol with improved security.	architecture and FL strategy for enhanced BTS.
[26], 2023	Implemented CNN based model for binary classification of brain MRI scans	Data augmentation, preprocessing and CNN model, MRI images from kaggle dataset	Limited dataset, need to add more datset for exploring additional tumor types in future work.	accuracy 94.51%, sensitivity 96.31% and specificity 92.51%
[27], 2021	E1D3 U-Net model for segmenting of brain tumor.	BRATS 2018-2021 dataset	Residual connections and deep supervision is missing in architecture, need to add them for increasing the memory	BRATS 2018 get WT, TC, & ET dice scr, 91.0, 86.0, and 80.2, while BRATS 2021 give 91.9, 86.5, and 82.0.
[28], 2021	VGG-SCNet transfer learning model is developed & comparative analysis of various transfer learning model undertaken.	VGG-SCNet transfer learning based model	-	Precision 99.2%, recall 99.1%, f1 scores 99.2%

2.4.3 UNET & Variant Based Segmentation Models

For precise classification it is essential to segment the image (i.e accurately segment the tumor area, enabling model to focus on region of interest) and then apply the CNN classifier. Without segmentation the classification model need to analyze the complete images including unimportant areas, noise, normal brain and background .The most adaptable segmentation model used for biomedical image segmentation is UNET model. Some of the key literature covering UNET and variant based models and general UNET architecture in Figure 2.4 is presented below. Baid et al., 2020 presented 3D U-Net network an innovative model design, for segmenting different types of tumors. The presented model is unique as it built 3D U-net with more filters at each level and fewer levels overall by using a weighted patch extraction techniques from edges of tumor. The N4ITK tool and normalization were employed in the pre-processing phase. Using the BRATS 2018 dataset, dice scores mean value for ET, WT, and TC were 0.75, 0.88, and 0.83, correspondingly[32].

Alqazzaz et al., 2019 proposed the SegNet architecture by training it using flair, T1, T1ce, and T2; four modalities of MRI images separately. The model have a pair of encoders for performing the down sampling operation, the encoder part has 13 feature operation blocks with 3x3 sized kernel and layers for max pooling operation.The decoder part of the model performed up sampling operation followed by same 13 convolutional blocks as in encoder section. The preprocessing steps include image normalization, matching, and bias field correction techniques. By using the BRATS dataset 2017 the model attained dice score value of 0.81, 0.85, and 0.79 for tumor core, whole tumor and improving tumor respectively. The model limitation is the training time latency problem, the study suggested that by employing better post-processing techniques in the future can improve the model accuracy significantly [33].

In another study Ahamed and Hossain et.al 2023 presented a comprehensive review of about more than 100 recent papers on deep learning based federated learning methodologies that showed signification improvement in image classification and segmentation tasks. The BraTS (2012 -2021) challenge and ISLES (2015,2016,2017) data set is utilized by most of researchers. The study highlighted several challenges of location uncertainty, morphological unreliability, low contrast,biased footnote, class imbalance and lack of clinical implementation. Among various segmentation approaches cascaded networks and ensembling techniques achieved exceptional performance in most accurate tumor segmentation, while fusion and attention mechanism can enhance the segmentation results on missing modalities. Dice coefficient metric is used as an evaluation metric rigorously. In upcoming years, FL techniques anticipated to be applied for wider range of medical software therefore there is need for developing more sophisticated protocols with enhanced security and privacy considerations [18].

Bukhari et al.,2021 presented a fascinating E1D3 U-Net, an improvement to the popular 3D U-Net architecture developed for segment brain tumors, which comprises of single encoder and three decoders. The two additional decoders in the architecture are designed similarly to the original encoder in the baseline encoder-decoder architecture. The final architecture consists of one encoder and three decoders, each of which gets feature maps from the encoder separately and generates segmentation at the output. They set the mean and variance of each 3D MRI volume in the whole-brain region to zero before training and testing. The study compared the dice scores from the BRATS 2018 and BRATS 2021, the results show that the BRATS 2018 dataset obtained WT, TC, and ET dice scores of 91.0, 86.0, and 80.2, while the BRATS 2021 dataset give 91.9, 86.5, and 82.0 respectively. However the proposed architecture lacks certain widely used components such residual connections and deep supervision which could significantly increase the memory [27].

Al-Ani et al.,2023 identified the key components for designing a deep learning model for brain tumor segmentation. It contain four main stages as shown in Figure 2.3 .The first stage is generally the dataset input. The dataset commonly downloaded from the dataset website and then goes through the data augmentation and image preprocessing phase to refine and enhance the dataset. The preprocessing can be done by removing the noise and resizing the image, while data augmentation performed through mirroring, flipping, rotating and cropping ect. Then some deep learning model is chosen for segmentation of tumor purpose. The model output is a binary classification i.e normal or tumor. The transfer learning is an optional stage in most of the studies because it can be used as an alternative of data augmentation technique for improving the model performance [10].

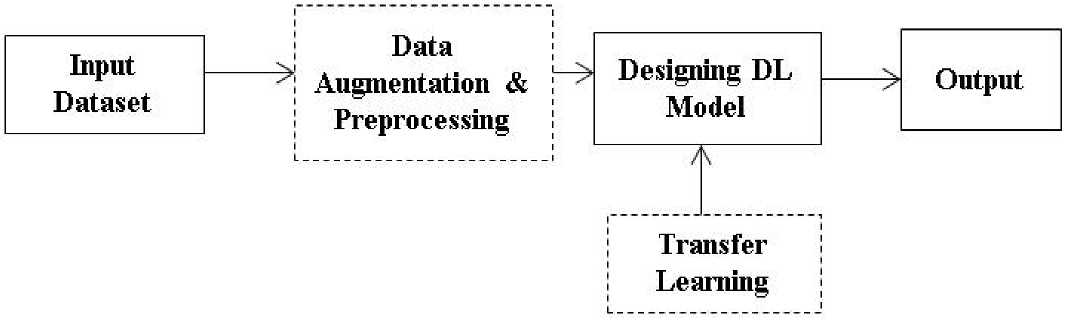

Figure 2.3: Designing of DL model block diagram

The review examines the findings of Abidin and Naqvi (2024). The study explores the various MRI modalities like T1, T1ce, T2 and flair along with their characteristics and employing these modalities in segmentation of brain tumor. The paper identifies the statistical analysis of recent studies, popular datasets, and evaluation parameters applied to the multi-model segmentation of brain tumor to notice recent developments, dynamic trends and evolution in the field. The deep learning segmentation models based on MRI modalities are categorized into CNN , Hybrid and transformer based models are reviewed from 2021 to 2013. Almost 97% of the researchers have chosen BRATS datasets of 2018, 2019, and 2020 versions.Furthermore, and in depth overview of standard evaluation metrics, DSC, accuracy, precision, recall, IoU is provided for evaluating model performance.The The development of model for precise brain tumor segmentation is a complex task. The author addressed the open research challenges, including Incomplete modalities since it is impractical to acquire all of the modalities, limited labeled data, improving model deployment and efficiency, interpret-ability and class imbalance, and suggested the potential solutions for handling these issues [40].

Additionally, Aarthia and Theresa (2022), for automated brain tumor detection introduced a novel segmentation-based classification method named DRLSTM. Initially, data cleaning has been carried out by eliminating noise using Convoluted Gaussian Filtering (CGF) method. It obtain the more clear texture patterns of images as the model's learning and classification mainly depends upon the input training data quality. Then segmentation is being carried out after preprocessing that segments an image into non-overlaping regions, which helps in minimizing the computational complexity of model. Various features such as mean, entropy, contrast and correlation are derived from segmented images. Lastly these features fed into classifier DRLSTM for training and binary classification. The model achieves an accuracy of 99%, outperforming other models in comparison.Future work can focus on incorporating meta-heuristic optimization approaches in order to to advance and simplify the classification process [56].

Brain tissue segmentation from MR images contributes significantly to provide comprehensive quantitative brain analysis for precise diagnosis, detection, and categorization of brain malignancies. Liang (2024) notice that although there are many improvement in automatic brain tumor detection techniques but due to the presence of noise, blurriness and motion related artifacts automatic segmentation is still facing challenges. The author reviewed about 100 papers to find the various segmentation techniques. Most of the research was conducted on fetal infant and adult brain tissues by noticing their structural categorization and effectiveness. The study notices that despite of success in deep learning there are limited clinical applications. Future work include a wide range of segmentation methods, like those for brain tumors, and incorporating other methods like non-deep learning approaches may help in thorough understanding of the developments in MRI brain imaging [57].

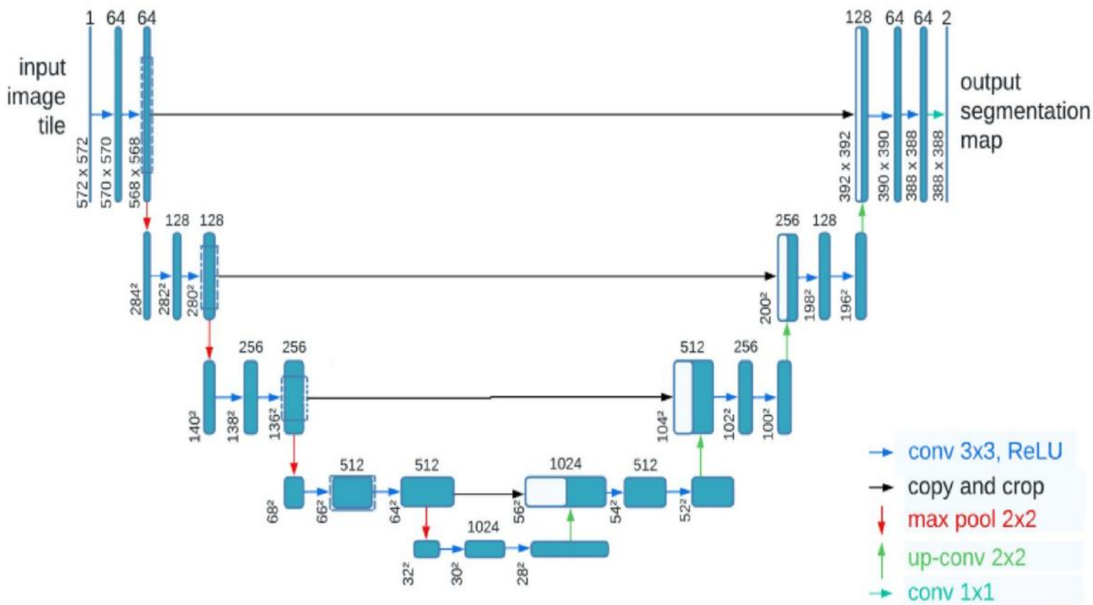

Figure 2.4: UNET architecture

Dorfner (2025) studied about the recent development in the field of deep learning in respect of brain tumor detection.various methods for MRI analysis like segmentation to define the volumetric analysis , response assessment and radiation planning, data preprocessing methods, and classification have been discussed. The study identifies the Resnet architecture most often used for feature extraction and UNET architecture for segmentation purposes. The future directions includes the use of quantitative MRI methods, integration of multimodalities, use of vision transformers architectures. The author also suggested to use foundation models are a new concept in deep learning , these are general-purpose models which are trained self-supervised on extremely large datasets of different datatype.The main challenges identified by the study includes limited dataset, bias and fairness, domain shift, generalizability, explainability and clinical translations [58].

In another study, Pranitha and Vurukonda (2024) achieved 98% accuracy with EL-DCLSTM model.The model has input layer, convolutional layer, pooling layer, LSTM layer, fully connected layer, and output layer respectively. Firstly, the images are preprocessed by resizing, cropping undesired areas, filtering and normalized for further processing. Then in second phase the advance UNET architecture most often used for biomedical image segmentation to detect the region of interest is used. The segmentation divides an image into different segments, using EPO's optimization with UNET the system outperform the segmentation by continuously optimizing the bias and weights parameter. The ResNet model is used to extract features in third phase and finally these features fed into EL-DCLSTM for classification purpose. The author find this model a most appropriate model as it combine the power of both convolutional and LSTM network to handle temporal and spatial information in MRI scans. The author compared the prosed model with other models such as DBN, Ab-RNN, CNN-LSTM, RNN-LSTM, and DCNN and the results shows a good comparative performance of proposed model. Despite of better classification result the model has some drawbacks. Its applicability to real scenarios , diverse dataset scalability is still a challenge [59].

2.4.4 Hybrid Deep Learning Models (CNN-LSTM, U-NET + LSTM)

To manage the constraints and limitations of standalone models, then new hybrid models that leverages the capabilities of multiple models have emerged. The literature on hybrid models have been extensively reviewed and analyzed below.

Saba, 2020 developed a grab cut method to accurately segment the actual lesion symptoms, and the transfer learning model visual geometry group (VGG-19) is fine-tuned to acquire the features that are then concatenated with manually created (shape and texture) features using a serial based method. The developed model is tested on different medical imaging database including MICCI challenge database including multimodel brain tumor segmentation (BRATS) 2015, 2016 and 2017. The dice similarity coefficient (DSC) testing achieved results of 0.99 on BRATS 2015, 1.00 on BRATS 2015, and 0.99 on BRATS 2017 respectively [31].

Various CNN architectures have been offered by researchers including AlexNet, VGG, GoogLeNet, Inception versions (v2, v3, and v4), ResNet, Res UNET and DenseNet models for brain tumor detection. The Res UNET depicted in Figure 2.5 contains residual blocks to learn residual mapping instead of feature mapping and thus leads to faster and optimized convergence during training. It also enhance the segmentation accuracy and model robustness. Cinar, et al., 2020 used an online dataset comprises of 253 images and proposed a hybrid CNN model for brain tumor detection. The model achieved an accuracy of 97.2% whereas 89.55% accuracy was obtained when they used AlexNet on their dataset [30].

However, challenges such as class imbalance and morphological variety remain significant hurdles. To address these issues, this study proposes an innovative approach integrating UNet and LSTM architectures with a mixed loss function. The author utilized an open-source brain tumor dataset and the proposed model achieved best performance compared to existing methods. Nevertheless, the study acknowledged limitations such as sample imbalance, thus addressed for future research involving cascade networks and segmented learning strategies. Additionally, the incorporation of GANs into the segmented network is suggested to mitigate over segmentation issues [29]. In another study Akter & Nosheen et al.,2024 presented deep CNN for tumor classification and UNET for segmentation tasks respectively. The deep CNN model is used for automatic classification of brain tumor into four main groups i.e glioma, meningioma, pituitary, normal brain and UNET model for image segmentation task is utilized, shown in diagram below. The study employed six benchmark datasets to test the CNN - classification and to train the segmentation model as well; alongside a comparison of impact of segmentation on tumor classification is also being conducted. Whether segmentation was used or not, there was not a noticeable distinction in the classification techniques but the no segmentation classification reduce the time required for classification. The CNN model obtained an accuracy of 98.7% without segmentation and 98.8% with segmentation method. The author suggested to consolidate more real-life MRI data for segmentation and training of the model, so that the model usefulness can be enhanced significantly in future [35].

A new framework You Only Look Once version 7 (YOLOv7) developed by Abdusalomov (2023). The framework incorporates the Darknet-53 backbone, PANet (Path Aggregation Network) Module, Convolution Block Attention Module (CBAM) attention mechanism and Spatial Pyramid Pooling layer in order to improve the feature extraction by allowing more focus on cancer-affected brain regions and to enhance the model's sensitivity by improving its detection accuracy and generalization. Decoupled heads are added to model, which enable the model to extract valuable insights from a broad range of data. Furthermore, a Bi-directional Feature Pyramid Network (BiFPN) is employed to improve the collection of tumor-related data and expedite multi-scale feature fusion. Dataset used in the study is openly available MRI dataset comprises of 2582 images of meningioma, 2548 images of gliomas, 2658 images of pituitary, and 2500 images of no tumors.These images enhanced, preprocessed and resized to 640x640 resolution. The data augmentation technique is employed to increase the variety of training samples dataset. The model compares with deep learning models like Xception, InceptionResNetV2, ResNet50,InceptionV3, and VGG16. The proposed framework achieved and accuracy of 99.5%. while the study provides value able insights, it is limited by using basic dataset and future research should be conducted by incorporating more clinically relevant range of brain lesions data for better real-world diagnosis [60].The use of deep learning approaches for image processing like image segmentation, object detection and classification has gain remarkable achievement. A hybrid DL CNN-LSTM model put forward by Rajeev and Rajasekaran (2023)for tumor classification. In the initial stage image pre-processing carried out using a hybrid Gaussian filter and wavelet filter for noise reduction and enhancing the image quality.Gaussian filter performs convolutional operation by multiplying image pixel values with kernels by eliminating noisy pixels while maintaining the general structure of the image's borders. The model uses transfer knowledge approach through an already trained Alexnet model for feature extraction. The ImageNet dataset containing over a million of images categorized into 1000 classes used to train the AlexNet model. it uses eight distinct layers and varying sizes of filters to extract meaningful information from input image. It uses a RELU activation function for introducing non linearity to the model a final fully connected layer extract the features which then fed as input to CNN-LSTM model for classification purpose. During training of CNN-LSTM model the hyperparamters are updated to optimize model performance, the loss function of cross entropy and Stochastic Gradient Descent optimizer applied for multiclass classification of tumor into four main classes i.e glioma, meningioma, no-tumor and pituitary.By leveraging the power of CNN model for classification and LSTM model that handles the sequential data processing the model achieved an accuracy of 97.94%, while showing good performance in comparison with other model like RF, KNN, and SVM [61].

Brain cancer is one of the most most dangerous brain malignancies, which can lead to incurable illness and even death if left untreated. A hybrid model developed by Prabu and Arasu (2024) by integrating long short term memory (LSTM) and gated recurrent unit (GRU).The study also contributed mainly in addressing several issues related to existing models. For noise reduction and data cleaning the images are preprocessed using Wiener filter which compares the input image to a noiseless image and eliminate blurriness in image. Then in next phase each images goes through segmentation process using watershed method. The LSTM model with multiple layers is developed and for feature extraction a pretrained ResNet50 model is used. These extracted features used by LSTM model to learn the temporal dependencies and patterns in the sequence of features. At the end classification is done by softmax activation function.In order to handle the issues of exploding gradient and gradient disappearance GRU is used. Future work can be carried out to focus on ROC characteristics in identification of tumor in low grade glioma images.Additionally, by incorporating more advance extraction methods and segmentation techniques can also help in enhancing the performance [64].

Ghassemi and Shoeibi (2020) used complex Generative Adversarial Networks (GANs) and pretrained CNN model that act as a classifier in model. A deep CNN network used to distinguish between real and fake images produced by the generator part of GAN. But due to inherent restrictions in GAN the input size was limited to a resolution of 64 x 64 [63].

Karac (2023) used a hybrid framework YoDenBi-NET to classify brain tumor such as glioma, meningioma, and pituitary brain tumor. The author presented two models, the first model uses YOLO detection algorithm to detect the affected brain region from preprocessed images. Then pre-trained CNN models are used for classification. While in second model,the features are extracted through pre-trained CNN models such as DenseNet201, ResNet50V2, InceptionV3, VGG 16 and VGG19, then extracted features fed into Bi-LSTM network for classification. The models are evaluated using tenfold cross-validation and hold out validation and has achieved the highest test accuracy of 99.77 and 99.67% respectively. In future work, the study aims to develop other robust model that can handle large dataset. Furthurmore, a two stages process, firstly segmenting brain tumor and subsequently detecting the tumor is recommended. This approach helps to increase the brain tumor identification and classification system applicability and accuracy [65].

A deep neural network ResNet was suggested by Hossein (2023) for brain tumor diagnosis. By leveraging the power of DCNN model with integration of features of Modified Ant Colony Optimization the model shows faster convergence and avoid local optima. The implementation results highlighted that how this method reduced the computation time while reaching 0.98% accuracy. Nevertheless, this model is not suitable for data sets that are imbalanced [66].

GANs and 3D ResUNet are two cutting edge technologies widely used for image generation, segmentation, and processing. H. Maeda (2021) introduced an innovative framework by addressing the issue of limited road damage training data in infrastructure detection. Multiple pseudo-images generated through adversarial networks (GANs) and variational autoencoders (VAEs) to overcome the problem of limited data. The generated images were closely resemble with real images. This solution significantly overcame data limitation issue and enhance model generalization ability [6]. Hamghalam, Wang, and Lei (2020) suggested a sequential GAN model to improve the input images contrast. By using this sequential model the computational time and complexity increase considerably, while it segment the tumors into three groups: enhancing tumor areas, core tumors, and complete tumors. GAN is used to generate images , and it took a long time of about 27 ms to generate a single high-contrast synthetic image. The hyperparameters used also increases like number of regions of interest (ROI) increases [62].

Sadafossadat Tabatabaei (2023) created a integrated framework to classify the correct tumor class by combining different DL architectures like CNN, self-attention network and Transformer model. Another enhanced CNN model was created for feature engineering in MRI images. Using a dataset of 3064 MRI images the framework shown an accuracy of 97.59%. In comparison with current models, the suggested methodology depicts reliable and precise diagnosis.However, there are considerable processing power and memory needs for this approach when employed with attention modules [67].

Marwa (2023) presented another deep learning brain tumor classification model. To maintain high efficacy and classification accuracies, the model combined DL model with meta-heuristic optimization algorithm. Using three databases of MRI images the model is trained and then a comparative analysis is performed with industry benchmarks like ResNet-50, DenseNet201, and MobileNet. Using coupling of Improved Hunger Games Search algorithm with residual learning model's features, the model significantly improve its accuracy rate. As per test outcomes, the model accuracy was 97.23%, 97.33%, and 99.41% in increasing order. However, the proposed approach uses a lot of resources and work and its also faces lack of interpret ability issue, which limits its utilization in actual clinical setup [68].

Ayesha Jabbar (2023) developed another hybrid deep learning model by combining CapsNet and VGGNet for automatic brain tumor classification by taking into account the problems availability of limited dataset. The proposed model is accessed using Brats2020 and Brats 2019 databases and evaluated different hyperparemters. So obtained an accuracy of 0.99% , sensitivity of 0.98% , and specificity of 0.99% on experimental data. Nevertheless, the study faces a limitation of high complexity and low generalizability [69].

Salehi and Baglat (2023) used LSTM model for binary classification in MRI images. The author reported that LSTM model when optimized with Stratified Shuffle-Split Cross Validation scored an accuracy of 98.62%. The images are converted to the desired shape for input to the model by considering each row of pixel in image is as a sequence. LSMT model designed to handle this sequential data, the LSMT model then captures the sequential patterns in data, by using a “return sequence” parameter the model handles the number of LSMT layers need to be added.The model uses multiple LSTM layers followed by dropout layer to avoid overfitting issue. It uses a sigmoid activation function for binary classification and binary-crossentropy for compilation. They also developed a web based application, that enables the user to upload MRI image and the model predicts the tumor is present or not. The author suggested that more efforts will focus on increasing the number of samples in dataset to make the model more generalizeable. However, they have applied the data augmentation technique to increase dataset size [70].

By considering six brain malagnancies including infract, hemorrhage, ring-enhancing lesion, granuloma, meningitis, and encephalitis Datta (2024) proposed CNN and RNN to detect and classify various brain abnormalities. CNN is used to extract key features of input signal and a many to many RNN is used but RNN faced an issue of vanishing gradient on small weight changes. So to mitigate this issue the author used RNN based LSTM.The structure of LSTM contains input, output and forget gate. The features of CNN and RNN based LSTM are then combined to make a hybrid model.The suggested model improves the efficiency in detecting and classifying abnormalities by integrating CNN and RNN-based LSTM techniques. To access the performance metrics like mean square error (MSE), probability of occurrence (POC), accuracy, and precision are evaluated.While comparison standalone CNN, RNN, and LSTM methods, the proposed technique perform better classification [71].

In (2022) Aqeel and Hassan employed LSTM model to detect biomarkers and deep neural network for classification purpose. Overall, their investigations investigated that RNN-based methods have remarkable results in Alzheimer’s Disease prediction. These models show an accuracy ranging from 86% to 99.2%. Furthermore, their applicability can be enhanced using bigger datasets in future. They finally reported that RNN-based methods have shown good accuracies while prediction of Alzheimer’s disease, and additional research in this filed has potential to considerably advance science [72]. While in another studies, Shoeibi and Khodatars (2023) explore the benefits of deep learning models by combining neuroimaging modalitalities. Various deep learning models such as CNN, RNN, GANs and AEs are investigated and compared with traditional approaches [25].

Montaha and Azam (2022) employed TD- CNN-LSTM and 3D CNN using four MRI sequences named T1 weighted, t1 weighted contrast enhancement, T2 weighted and flair for binary classification of brain tumor. Their developed model TD-CNN-LSTM achieved a test accuracy of 98.90%. The dataset BRATS 2018, 2019 and 2020 comprises of 282,331 and 365 images. All the dataset have been preprocessed to normalize and re-scale, for training purpose Brats 2018 and 2019 versions are used whereas 2020 is used to test the model. The model mainly comprises of four units; 2D convolution for extracting features, pooling layers for feature reduction, LSTM and finally a classification layer. A time distributed function is used to reduce the model complexity. By employing the K fold cross validation method the model is more robust and reliable in different training scenarios. In future work, by combining all the MRI sequences and using CNN model along with ablation studies could be a promising approach to significantly minimize computational time while achieving high accuracy [22].

Brain tumor is the most serious disease and can lead to death if left untreated, therefore its early prognosis is crucial. Maqsood and Robertas (2022) finds that manual techniques are error prone and monotonous, therefore there is a pressing requirement of automated solutions. He presented a novel approach that make use of CNN, MobileNetV2 and SVM classifier. Their methodology have five main steps including linear contrast stretching, image segmentation using CNN, feature extraction employing MobileNetV2, best features selection using multiclass support vector machine and finally tumor classification. BraTS 2018 and Figshare datasets were used in this work. Their proposed approach achieved a detection and classification accuracy of 97.47% and 98.92%, respectively. This is highly suitable method as it has less computational time along with quicker convergence. Furthermore, entropy based best features selection method extracts only the highest priority features by discarding unnecessary and redundant features. The limitations of the study includes use of 2d MRI dataset and more time consuming feature processing steps. Therefore in future work 3d MRI images should be used for more effective segmentation process [20].

Neetha and Narayan (2024) suggested a novel method for accurate brain tumor segmentation name LRIFCM is developed. Three various dataset BRATS 2017, 2018 and figshare is used that includes Flair, T1, and T2modalities. The figshare dataset has 3064 T1-weighted contrast MRI scans. It has 708 images of meningioma, 1426 images of glioma and 930 images of pituitary tumor respectively. Segmentation is carried out using and improved LRIFCM which incorporates Local Intensity Distribution Information (LIDI) and regularization parameter. The LRIFCM has improved the results by highlighting the tumor edges even of intrinsic nature of tumor. Then classification is being carried out by LSTM classifier. The classification accuracy of the model is 98.73% showing a comparatively good performance than other Hybrid-DANet, TECNN and VAE-GAN models [15].

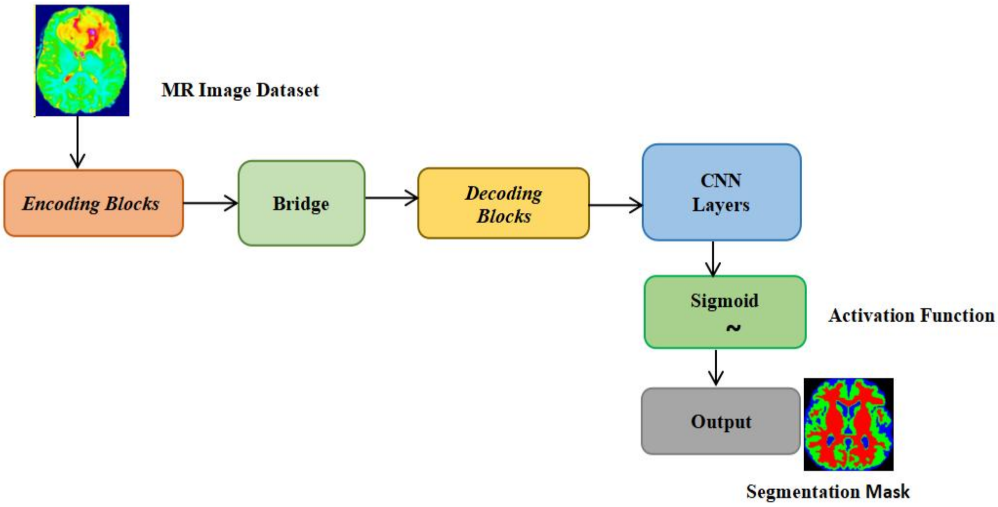

Figure 2.5: Res-UNET model structure

Jian and Haq (2022) introduced a framework to detect brain cancer malignancies in Medical Internet of Things healthcare systems. The system based on hybrid CNN LSTM model which uses CNN comprising of many convolution layers to extract deep and complex features and then these features fed into LSTM for further classification. Before passing the image data to CNN data transformations are applied to increase the number of samples. During training the hyper parameters like batch size, epochs, learning rate and number of layers in CNN and LSTM are updated for better model performance. It uses the hold out cross validation method for testing and validation purposes. The whole experiment conducted on computer with a GPU and window 8 operating system. The software implemented using 3.7 python version, tensorflow 1.12 and keras 2.2.4. Performance of CNN-LSTM model on various original and augmented dataset is separately evaluated and obtained an average accuracy of 98.78% on original dataset and 99.39% on augmented dataset. The comparison results demonstrated that developed network obtained accuracy of 99.93% on BTDS dataset, 99.22% on MBNDS dataset and 98.67% on BMIDS dataset showing relatively improved outcomes than other state of art methods. As a future work, the proposed framework will be use to detect other illness like lung cancer, breast cancer, heart disease, Parkinson's disease, and diabetes.we also propose to make use of transfer learning approach, deep learning and federated learning approaches for classification and detection purposes that uses internet of Things (IoT) [11].

Table 2.3: Summary of discussed literature related to hybrid models

Ref	**Purpose**	**Classifier& Dataset**	**Limitations / Future work**	**Results**
[35], 2024	CNN model for tumor classification and UNET for segmentation tasks respectively.	Six benchmark datasets	Incorporate more real-life MRI data for segmentation & training tasks to increase model usefulness.	The CNN model ACCU 98.7% without segmentation & 98.8% with segmentation
[36], 2024	Proposed hybrid model to study brain tumor & stroke image generation & lesion segmentation.	3D ResU-Net & GAN, Use of Flair T1, Flair T2	The clinical data available for experimentation is limited and hence improvement needed	HD index value 75.082, precision index value of 0.696.
[29], 2021	Hybrid model for BTS & overcome the issue of class imbalance along morphological uncertainty issue	Hybrid model UNET + LSTM Open source brain tumor dataset	Sample imbalance issue, need cascade networks & segmented learning strategies for handling it	Model achieved best performance over traditional segmentation methods
[30], 2020	Hybrid CNN model for automatic brain tumor detection	Hybrid CNN model AlexNet online dataset	-	97.2 % ACC, AlexNet ACC 89.55%
[31], 2020	Transfer learning model VGG-19 is fine tuned to get the shape and	VGG-19 (BRATS) 2015, 2016 and 2017, MICCI challenge	-	DCS 0.99 for BRATS 2015, 1.00 for BRATS 2015 dataset, & 0.99 using BRATS

	texture based features			2017
[32], 2020	3D U-Net network With multiple filters at each layers for segmenting different types of tumors	N4ITK & normalization as preprocessing BRATS 2018 dataset	limitation of more time for training the model effecting the computational efficiency	dice scores for ET 0.75, WT 0.88, and TC 0.83
[33] 2019	Presented SegNet model for brain tumor detection	SegNet model, four MRI modalities BRATS 2017 dataset	Time taking training phase, recommended to perform better post processing techniques to achieve better results	Dice score of 0.81 for core of cancer region, 0.85 for whole tumor, 0.79 enhanced tumor.
[34], 2019	Developed 2D U-Net model regarding whole-brain tumor segmentation & intra-tumor region	2D UNET, BRATS 2018 dataset	Recommendation for GPU , enhancements for accelerated & more destructive model learning	DSC 0.805 for tumor core, 0.868 for whole tumor , and 0.783 for enhanced tumor

2.5 Comparison of Models

Table 2.4: Comparison of state-of-the-art approaches

Study	**Type of Model**	**Results (%)**	**Strengths**	**Limitations**
Kaya (2025) [54]	CNN+ Particle Swarm Optimization (PSO)	99%	Identification of best hyperparameters, higher accuracy and finding best performing model	performance degradation on noisy data
Saxena (2025) [45]	CNN model	97.87%.	Simple and reduced workload	Need for large annotated-dataset
Pranitha (2024),	EL-DC LSTM + UNET + EPO's optimization	98%	Effective high level feature extraction, optimized performance	generalization issue across varied dataset

[59]			and handle temporal and spatial information	
Akter (2024), [35]	CNN +UNET	98.8%	Comprehensive examination of varied dataset, more holistic approach	Data limitations, less effective segmentation while processing time trade-off
Natha, 2024 [41]	AlexNet+VGG19+ CNN	98.75%	State of art accuracy	Require segmentation of affected area
Naeem (2023) [43]	MobileNetv2	99.83%.	Efficient in complex feature extraction	Require large memory, computational time/ complexity
Aarthia (2022), [56]	Segmentation + Convoluted Gaussian Filtering (CGF) method	99%	Minimum computational complexity due to precise segmentation, clear texture & data quality	in efficient classification process, need of manual hyper-parameter settings
Sharif, 2021 [37]	Densenet20 + Support Vector Machine (SVM)	95%	Improved accuracy	Longer training time, discarding important features
Bukhari , 2021 [27]	E1D3 U-Net (Encoder, Decoder)	-	Enhanced feature engineering and precise segmentation, good generalization capabilities on multiple datasets	computationally costly due to large memory requirements, difficulty in complex feature extraction
Wang (2020), [62]	GANs	-	-	Increased time and complexity

2.6 Research Gaps and Directions

Table 2.5: Research gaps and directions in literature

Author(s) / Yr	**Challenges in Brain Tumor Detection/ Classification Literature**	**Deep Learning Solution**
Murshidawy and	The heterogeneity of tumor morphology	Use Mutimodel Based Approach,

Shamma, 2024 [13] Rafi ,2022 [9], Ahamed,2023 [7], Akter, 2024 [28]	in medical imaging makes it hard to use prior facts on relative tumor appearances due to variety of tumor types and their aggressiveness [13]. Morphological uncertainty and the intensity level of tumors. [9][7] Wide variety of tumor locations, shapes, and structures[28]	Increasing the depth/layers of model, Incorporate a weighted loss function [9], assign special weight for the background labels during segmentation giving more importance to accurately identifying the boundaries between touching tissues. [7]
Shamma, 2024 and Alqazzaz 2019 [19],[33]	Limited Labeled Image Dataset, Gathering labeled dataset is costly and difficult.	Incorporate data argumentation or transfer learning[13] Perform Patch-wise training[27]
Al-Ani and Al Shamma, 2023 [18]	Overfitting issue if model learns the training data too well, resulting in bad performance on unseen/new data.[18]	Incorporate data argumentation or parameter tuning [9] Use transfer learning or drop out function to improve generalization of model [13].
Saeedi and Rezayi 2023, [12], [8]	Class Imbalance where one class (the majority class) has significantly more samples than one or more other classes issue in medical imaging [12] Insufficient Labeled data issue [9]	Use of GANs to generate synthetic samples for the minority class, which can help balance the class distribution [8]. Use transfer learning, sampling techniques, use a well-trained model or dice loss function [26] [9]. Utilize data augmentation techniques [9]
Ahamed, 2023 [7]	Low Contrast between the tumor location and surrounding normal tissues thus making it difficult for algorithm to detect and segment tumor. Annotation Bias occurs by segmenting the tumor location manually so depends upon the radiologist experience [7]	Data Augmentation, Transfer learning, Normalization. Sampling Techniques, Weighted Loss Function, Ensemble Learning
Rafi ,2022 [9]	Most deep learning research is Supervised Learning based Research [9] [13],[19] Lack of clinical implementation [7]	Pay attention to unsupervised & semi-supervised learning for unlabeled data[9]. Resolving Communication gap between developers & clinical professionals effectively.

2.7 Summary

This chapter offers a comprehensive examination of the research background information, existing approaches their validation and constraints pertinent to the study, encompassing existing literature on CNN models, hybrid models and traditional machine learning models. It also examines complementary research and technologies aimed at identifying brain malignancies.

CHAPTER 3

METHODOLOGY

3.1 Overview

This chapter covers research methodology, detailing the methodology steps and rationale for the methods selected to meet the research targets. The research develops a hybrid deep learning model by following model development life cycle including data acquisition, data preprocessing, feature extraction, model designing, training, testing and optimization. Additionally, it outlines the tools and framework utilized for implementation and evaluation process of the model, including the primary language, online platforms, techniques , libraries and models used.

3.2 Context

This research delves hybrid deep learning model's prospects in brain tumor detection and classification. Firstly a standalone LSTM model is implemented for detection and classification of brain tumor. Secondly a hybrid UNET+ LSTM model is being developed for achieving the research objective. UNET contains a series of convolutional and upsampling layers for capturing intricate spatial features from MRI images. These features then fed into LSTM input layer after flattening, which learn from these sequence of patterns and outputs the classification results. The LSTM contain multiple LSTM layers followed by batch normalization and dropout layers to stabilize training process and avoid overfitting. The training process monitor and optimize using early stopping, call backs and learning rate scheduling mechanisms. After training both models performance is evaluated using F1 measure, accuracy, precision and recall. This research highlights and contributes to the effectiveness of hybrid deep learning approaches in automated medical imaging analysis and classification tasks.

3.3 Experimental Setup

The model development is is carried out using online platform google colab with GPU runtime. Colab is an open source freely available platform which provides hosted jupyter notebook.It is mostly used for data science, machine learning, and research projects. Python is used as a primary language for implementation of model. Various libraries including tensorflow and keras, Numpy, Pndas, Sklearn, matplotlib, and seaborn were utilized. The datset is preprocessed , normalized by ImageDataGenerator class and split into test train and validation splits.The model training is optimized and adjusted using ReduceLROnPlateau and EarlyStopping callbacks to prevent over-fitting and enhance performance. Colab's hardware and runtime environment provided the resources required to implement successful deep learning model training.

3.4 Dataset

The dataset sourced from online platform - Kaggel , which provides access to machine leaning resources and open-access datasets. The MRI brain image based dataset is obtained, comprising of four different classes: Glioma (926 images), Meningioma (926 images), Pituitary Tumor (926 images), and No Tumor (926 images).

The images were organized into training and testing folders, each having four sub folders for each tumor class. The images in training sub folders have their respective class labels while images in testing sub folders have same common label. All of them were in grayscale and represented in coronal, axial, and sagittal plane. Figure 3.1 shows some of the images of different classes of tumor. The python ‘os’ module and pandas library is used to traverse through directory structure and generate Dataframe table for organizing the image file paths and labels. The Dataframe organizes the data into rows and columns and thus enables effective data processing and manipulation.

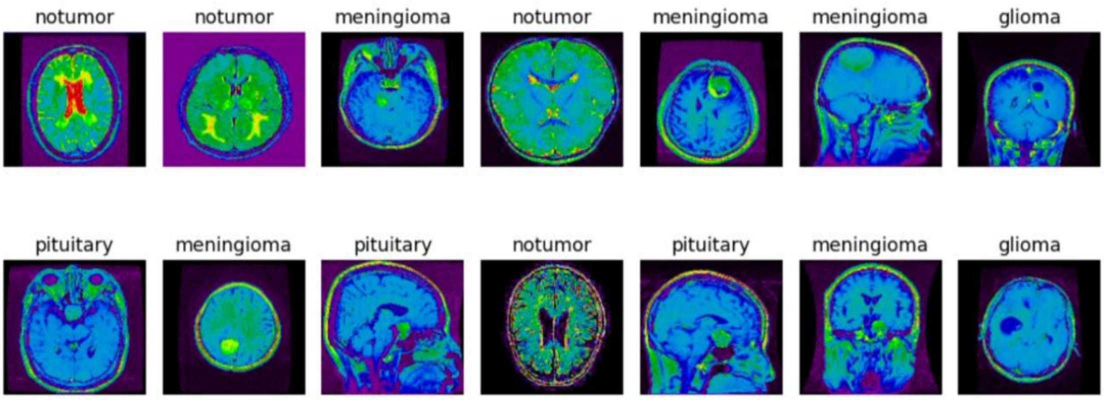

Figure 3.1:MRI Dataset of different tumor types

3.4.1 Dataset Distribution

Training, validation and test sets make up the dataset. The training dataset applied for model training, while validation set is utilized to access model and hyper-parameter tunning; whereas test dataset is utilized for making model's predictions.The training dataset undergo 80-20 split ratio using sklearn library train_test_split function, so 80% of the data is reserved for training while remaining 20% is taken for validation purpose.

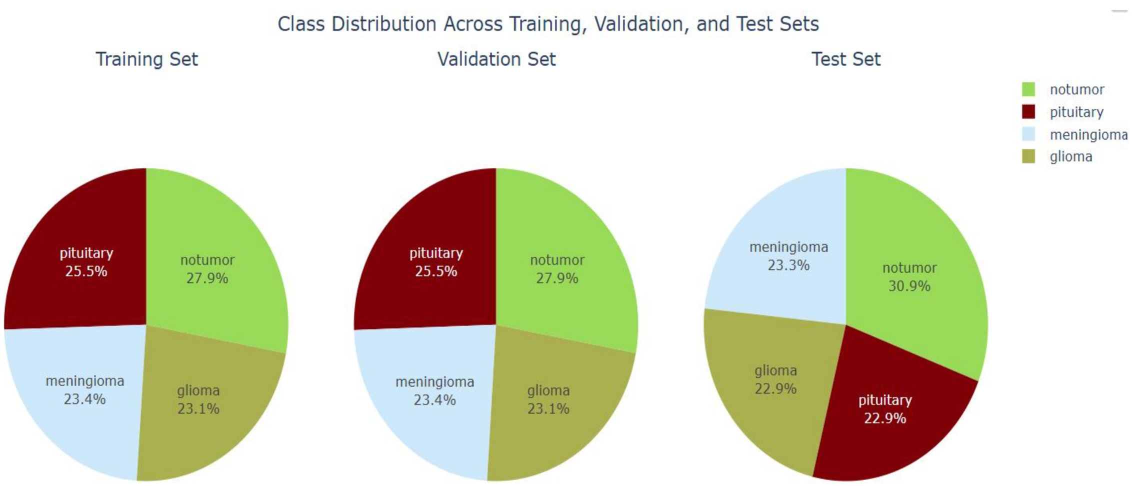

Figure 3.2: Training, validation and test set data distribution

The test is used as it is since it is used for testing the model The pie charts are created to visualize the class distribution for training, validation and test split using python's Plot library. These percentage of each class is displayed to provide a quick understanding of data division. Figure 3.2 displays the generated pie chart for data distribution of different sets.

3.4.2 Dataset Pre-processing and Augmentation

The all three datsaets were preprocessed and normalized to make them suitable for model's input. The dataset of four classes, their categorical labels are converted to binary vectors by defining class_mode='categorical' in the dataset preprocessing steps. This generates the binary vector for each class such as for glioma [1, 0, 0, 0], Meningioma [0, 1, 0, 0], Pituitary [0, 0, 1, 0], and No Tumor [0, 0, 0, 1]. The images were gray scale and resized to (128 x 128) pixels to prepare them for input to the model. The re-sizing is important as the model input layer require only fixed size input, it is done to set the same width and height (i.e 128 x 128) for all the images. This help in optimization and speed up the training process. Then the images were re scales using ImageDataGenerator class of TensorFlow to normalizes the pixels values. By dividing each pixel value by 255 using rescale=1./255 parameter in ImageDataGenerator , the pixels are transformed to a range of [0 , 1] from [0 , 255]. The color channel is set 1 for gray scale MRI images, which reduces the computational complexity while preserving the spatial details. For effective memory utilization, a batch size of 32 is set to process and learn 32 images at a time by the model.

To provide model with more diverse dataset and to improve the generalization of model, different data augmentation methods were applied on training set. This will help to significantly artificially increases the count of samples for the model to learn and generalize well. The geometric transformations, such as rotation by 30% , shifting the images 20% along height and width, displacing images pixels in various direction and distorting them by shear transform. The images are further zoom in and out by 20% and flip horizontally along with shuffling them randomly. Then Python's itertools.cycle is used to iterate over each class and to make sure that no any class is underrepresented and overcome class imbalance issue. Generated images are reshaped to size model input size i.e 128 x 128 and falttened into 1D array for input to LSTM model for classification. The augmentation help in handling with the problem of class imbalance issue as it augment the dataset two times and produces 5,740 images. Some of the random images after augmentation results are shown in Figure 3.3.

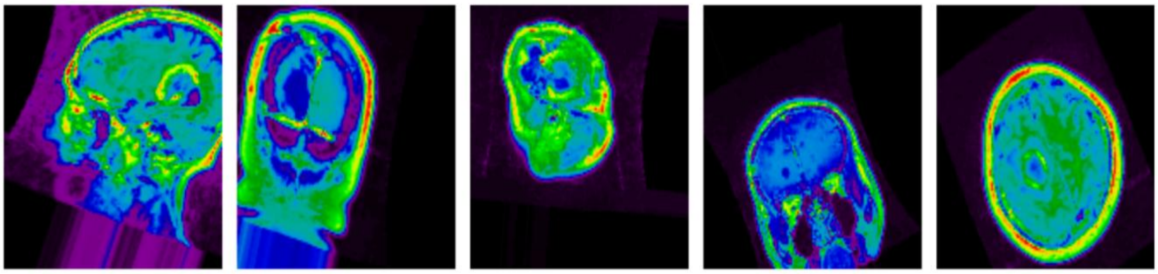

Figure 3.3: Data augmentation MRI image

In order to maintain the data integrity, test and validation datasets do not undergo augmentation process. Since testing and validation sets are representation of real world data and used to evaluate model performance on these unseen datasets.

3.4.3 Image Batching and Startified Sampling

Startified sampling is a sampling technique used to split the dataset in a way that every split contain equal distribution of each class as in the original dataset. Using sklearn 'train-test-slpit' function it split the dataset into test and train split with a proportional distribution of dataset for all four classes. It is especially useful for handling imbalanced dataset. Images are loaded in batches instead of loading all images at the same time into memory. Image batching process efficient memory utilization, faster training and speed up convergence.

3.4.4 Bias Field Correction Preprocessings

The images obtained from different scanners often have variable intensities. Bias field correction is a preprocessing technique used to eliminate these intensity inhomogeneties and non uniform illuminations by ensuring consistent intensity for all tissues across image.

N4ITK preprocessing is employed to normalize the intensity variations in images. It removes the low frequency intensity variations from the images and normalize intensity.

3.5 Proposed Deep Learning Models Design and Development

This research composed of two advance deep learning model for automatic brain tumor detection and classification. In the first part, LSTM model is developed with multiple LSTM layers which effectively processes sequential MRI images. It reshapes images to sequential patterns, considering rows as time steps and columns as features. In the second part, a hybrid model by integrating UNET and LSTM is designed to carry out segmentation, feature extraction, tumor detection and classification. After that these models conscientiously evaluated and their performance is compared with existing models.

3.6 Model 1 (LSTM) Design

The model uses a dataset comprises of 5,712 MRI images for training and 1,311 for testing purpose. It has various layers, possessing input layers, LSTM layers, pooling layer, fully connected and dense layers. The input layer specify the shape of input data, as LSTM expects only sequential data therefore images are flattened to 1D array to get time dimensional data. Each 2D MRI image (i.e 128 x128) is transformed into single sequence vector by treating rows as time steps, and columns as features. The first LSTM layer is defined with 512 hidden units (i.e memory units) makes this layer to learn 512 distinct features at each time step by setting return sequences=true. This return_sequences=true ensure that every single time step in LSTM generates a sequence for next layer instead of single value.

Moreover, two LSTM layers included 256, 128 hidden units, and others have 64 with each having the same configurations. The final two layers included fully connected and dense layer with 64 and 4 hidden units. The fully connected layer with ReLU activation function, introduces non linearity to the model and captures complex patterns in the data. This network learns sequential patterns from MRI images. The layers are connected with each other, each layer extract temporal dependencies from sequential data and pass this information to next layer. The network has total four LSTM layers, one fully connected and one output layer. The final output layer perform classification using softmax activation function, have 4 output units. In this process, the batch normalization layer is is used to stabilize learning by normalizing output and improving training performance.A dropout layer with a rate 0.3, and L2 regularization technique were also used.To enhance the efficiency, the Adam optimization function is used. The learning rate parameter is tested with different values and 0.001 was found to be the suitable choice.The training process was accomplished after 50 epochs, having 100 steps in each epoch. The batch size of 16 is determined and each epoch takes an average of 13 sec to process.

The summary of learning parameter of proposed LSTM network is given in table 3.1.By taking up the sum of values in Param# column , a total number of 106,937,550 parameters were determined. In which 35,645,252 are trainable parameter while 1,792 are non-trainable parameters. There are 71,290,506 more parameters in the optimizer for adaptive learning adjustments.

3.6.1 L2 Regularization for Addressing Over-fitting Problem

The L2 regularization is applied to prevent overfitting and improve the model generalization capabilities. L2 regularization also known as Ridge Regularization. Regularization method imposed constraints on model's weights, thus improving the model generalization for unseen data. In order to reduce the possibility of the model's issue of fitting noise during training phase, L2 regularization was deliberately asserted.

3.6.2 Dropout Regularization to improve Generalization

Dropout regularization technique is employed to further prevent overfitting by discarding a fraction of neurons while training. The implementation of this regularization methods is demonstrated in Figure 3.4. This technique reduces dependency on specific neurons and ensures that every neuron contributes equally for making decisions. The dropout of 0.3 is applied to randomly drop 30% of neurons during training, thus makes the model to learn more varied and robust features. During testing and prediction all the neurons contributes for decision making and dropout is kept turned off. Without dropout function the model could memorize the training data rather than making generalization to new data.

```
def build_hybrid_model(input_shape, sequence_length, num_classes):

    unet_encoder = build_unet_encoder(input_shape)
    sequence_input = Input((sequence_length, *input_shape))

    encoded_sequence = TimeDistributed(unet_encoder)(sequence_input)

    # TimeDistributed applies the U-Net encoder to each image in the sequence
    flattened_sequence = TimeDistributed(Flatten())(encoded_sequence)
    lstm_output = LSTM(64, return_sequences=False, dropout=0.4, recurrent_dropout=0.4)(flattened_sequence)
    classification_outputs = Dense(num_classes, activation='softmax')(lstm_output)  #tumor classification

    unet_lstm_hybrid_model = Model(sequence_input, classification_outputs)
    return unet_lstm_hybrid_model

# Build and compile the hybrid model
unet_lstm_hybrid_model = build_hybrid_model(input_shape, sequence_length, num_classes)
unet_lstm_hybrid_model.compile(optimizer=Adam(learning_rate=1e-5), loss='categorical_crossentropy', metrics=['accuracy'])
```

Figure 3.4: Regularization techniques

3.7 Model 2 (Hybrid UNET + LSTM) Design

The main objective of this research is to develop a hybrid model, specifically aimed to address the challenges found in past studies and to overcome the misclassification rate problem found in model 1 (i.e LSTM model).The proposed model represented in Figure 3.7 integrate UNET and LSTM for automatic brain tumor classification into four main categories (i.e glioma , meningioma, pituitary and no tumor). UNET is a fully convolutional neural network consist of an encoder part which is also called contraction path, having many convolutional and pooling layers and is responsible for capturing important context from MRI images.The feature map captured by the model at various convolutional layers is illustrated in figure 3.5, where the extraction code screen shot is provided in Figure 3.6.

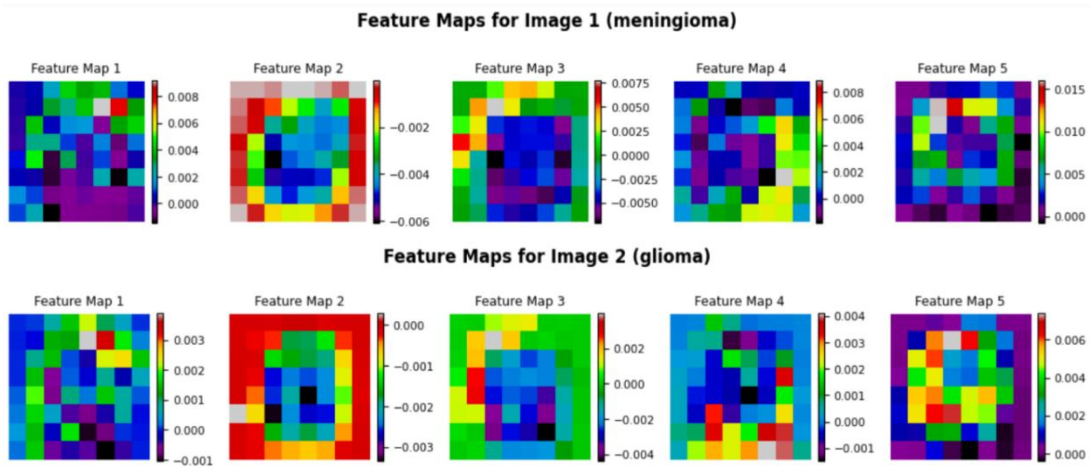

Figure 3.5: Feature map of MRI images

The sequential MRI images are loaded in batches using SequenceDataGenerator class to process effective data flow during training. Then images labels are converted to one-hot encoding using to_categorical() to convert the image's labels into vectors. The shuffling is performed after each epoch using random shuffle method which enables to creates varied training batch for improving model generalization.

```
#prepare a feature map
feature_extraction_model = Model(inputs=unet_lstm_hybrid_model.input, outputs=unet_lstm_hybrid_model.get_layer(index=1).output)
X_batch, _ = train_sequence_gen[0]  # Take the first batch

# Extract features directly from the existing model
extracted_features = feature_extraction_model.predict(X_batch)

print(f"Extracted feature shape: {extracted_features.shape}")

def plot_feature_maps(features, labels, num_images=6, num_maps=5, colormap='gray', figsize=(11, 8)):
    for img_idx in range(num_images):
        plt.figure(figsize=figsize)

        # Get the class label for the current image
        class_label = np.argmax(labels[img_idx])
        class_name = [key for key, value in label_map.items() if value == class_label][0]
```
Figure 3.6: Extracting feature map in UNET encoder

3.7.1 Convolution Blocks

The feature extraction is carried out by four convolutional block with 64, 128, 256 and 512 filters are used to extract specific features. The number of filters increases in each progressive block enabling the network to learn more complex patterns. A filter size of (3, 3) is chosen. The convoultional operation is performed by sliding these 3x3 filters over the image, the image pixel values are multiplied with filter pixel values and thus a resultant feature map is generated.Various patterns, edges and textures are detected in this phase. To carry out different characteristics from the input MRI images including basic to advances complex features the selected networks is carefully designed, so that more precise classification could be performed. Zero padding is applied to maintain the size of input feature map so each convolutional operation produces the same size output as the input.

3.7.2 Max Pooling Layer

Encoder downsampling operation is performed for reducing the size of feature map but maintaining the important details. Height and width of feature map is reduced by factor of 2 by defining max pooling with pool size of (2, 2).These pooling layers helps to significantly reduces computational complexities, and assist model to detect multiple patterns regardless of their locations.Max pooling layers with CNN emphasizes extraction of important features like borders and significant textures, while diminishing effects of unimportant differences.

3.7.3 Model Training

Each convolutional block followed by batch normalization layer and LeakyReLU activation function to get a stabilized feature learning process during training.The network overall contains four convolutional block with varying filter size. The first block takes input image and process it to feature map which then passed to the next block. Each block output is fed to next block as input to get more abstract feature map. By doubling the number of filters in each block this design continuously learns and train from more complex details. The final layer then input last generated feature map and perform classification on it.

The model is trained for 50 epochs, during training it uses the train set to learn various patterns and dependencies of it, the code snippet portrayed in Figure 3.8 demonstrates its implementation. Each passing epoch computes the accuracy, loss and learning rate, the loss computed from the last epoch is then provided again as feed back to the model. Thus model keep learning from feed back and continuously improves its performance.

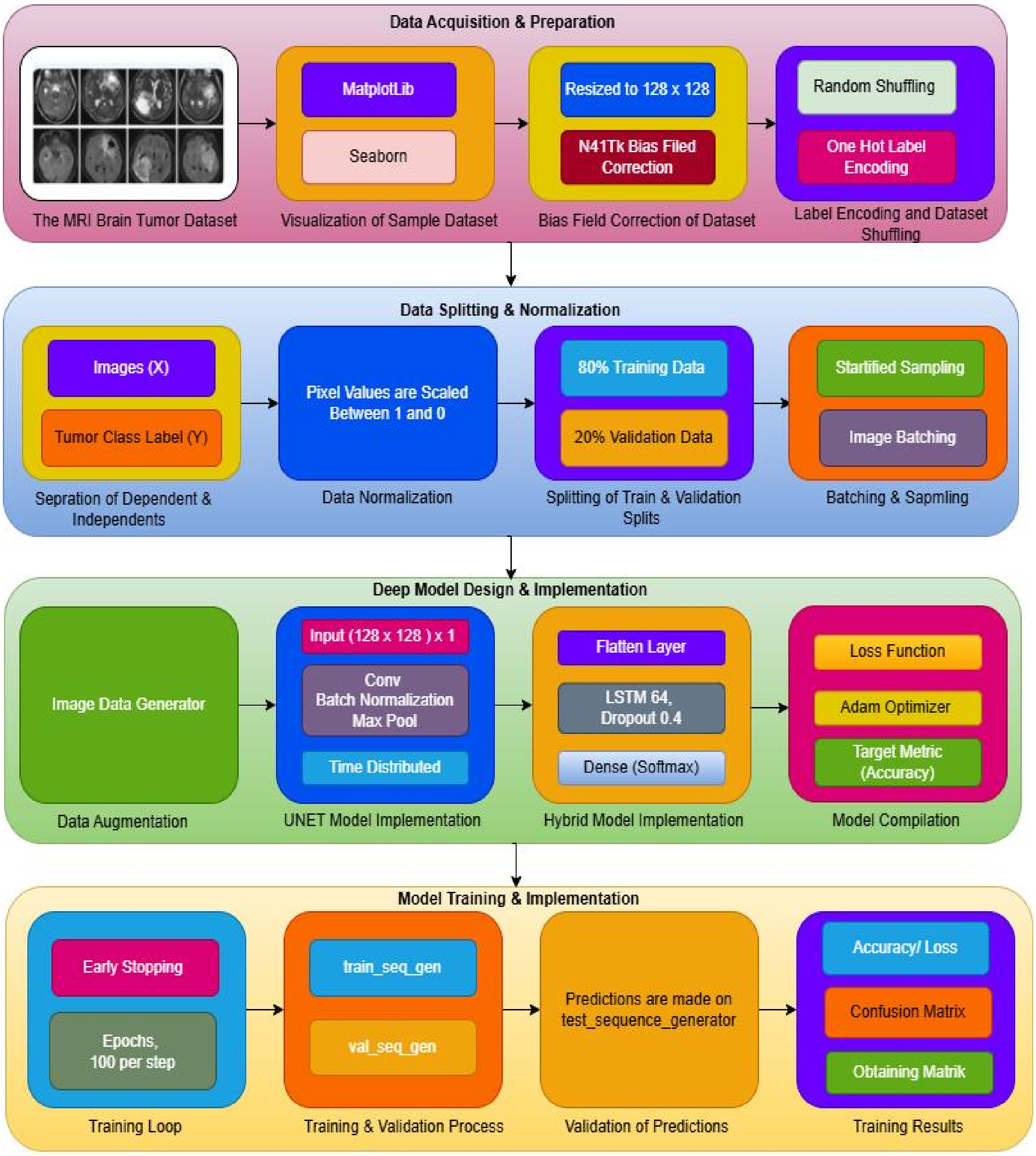

Figure 3.7: Proposed hybrid model flow diagram

For activation function 'softmax' is chosen and 'adam optimizer' with learning rate of 0.00001 was utilized. Total 50 epochs with early stopping mechanism and patience of 5 is set to monitor the validation loss parameter, which denotes that if training process does not decreases the validation loss for consecutive 5 epochs then stop training. Shape of 2D input images is 128x 128 x 1 where 1 denotes channel of image and 128 x 128 represents the height x width of image.

```
# Model Training with Early Stopping
early_stopping = EarlyStopping(
    monitor='val_loss',
    patience=5,
    restore_best_weights=True
)

# Training the hybrid U-Net + LSTM model
unet_lstm_hybridModel_history = unet_lstm_hybrid_model.fit(
    train_sequence_gen,
    validation_data=val_sequence_gen,
    epochs=50,
    callbacks=[early_stopping],
    steps_per_epoch=50,
    validation_steps=len(val_sequence_gen)
)

# Extract Training Metrics
unet_lstm_hybrid_model_metrics = {
    "unet_lstm_accuracy": unet_lstm_hybridModel_history.history.get('accuracy', []),
    "unet_lstm_val_accuracy": unet_lstm_hybridModel_history.history.get('val_accuracy', []),
    "unet_lstm_loss": unet_lstm_hybridModel_history.history.get('loss', []),
    "unet_lstm_val_loss": unet_lstm_hybridModel_history.history.get('val_loss', [])
}
```

Figure 3.8: Model training and history

3.7.4 Loss Function

Loss function calculates the difference between actual label and predicted labels that are generated by model as predictions. During training the model weights are updated based on calculated losses to optimize its performance through back propagation mechanism. At final phase, for multicalss classification of brain tumor, categorical cross entropy loss function is used, which is calculated by given formula.

L = −∑I=1 C yi log(yi)

C: represents total number of classes

Yi: denotes true class labels

Y^i: define the probability of predicted value for class

Table 3.1: Modified LSTM parameters to classify 4 types

Layer (Type)	**Output Shape**	**Param #**
Lstm_4 (LSTM)	(None, 1, 512)	34,605,056

Dropout_5 (Dropout)	(None, 1, 512)	0
Batch_normalization_3 (BatchNormalization)	(None, 1, 512)	2,048
Lstm_5 (LSTM)	(None, 1, 256)	787,456
Dropout_6 (Dropout)	(None, 1, 256)	0
Batch_normalization_4 (BatchNormalization)	(None, 1, 256)	1,024
Lstm_6 (LSTM)	(None, 1, 128)	197,120
Dropout_7 (Dropout)	(None, 1, 128)	0
Batch_normalization_5 (BatchNormalization)	(None, 1, 128)	512
Lstm_7 (LSTM)	(None, 4)	49,408
Dropout_8 (Dropout)	(None, 4)	0
Dense_2 (Dense)	(None, 64)	4,160
Dropout_9 (Dropout)	(None, 64)	0
Dense_3 (Dense)	(None, 4)	260

3.8 Model Performance Evaluation Metrics

The evaluation of both models is measured through standard evaluation metrics such as F1 measure, accuracy, precision and recall.These metrics are commonly used measures in medical image classification to assess the model's performance [12].The rationale for choosing any of these metrics is discussed in this section; each one contributes in a different way to an adequate understanding of the model's prospective.

3.8.1 F1 Measure

The harmonic means of precision and recall values, presents a equitable assessment metric combining both false positives and false negatives. It minimizes the false positive and false negative, thus providing a balanced measure of its ability for correctly identifying positive instances. The formula of F1 measure is as under.

F1 Measure = 2 × (Precision x Recall / Precision + Recall)

3.8.2 Accuarcy

It is defined as the overall correctness of model and is calculated taking division of correctly predicted instances by total number of predictions.

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

3.8.3 Precision

It calculates the ratio of correctly predicted positive instances among all instances that are predicted ad positive. If the model predicts yes, then how often it is correct is called precision of model and is calculated by the given formula. A high precision means low false positive rate. A false positive occurs when a model makes wrong class prediction for a sample but the sample actually belongs to another class. A model with high precision rate mostly often makes correct predictions.

Precision= TP / (TP + FP)

3.8.4 Recall

Recall is a performance evaluation metric that calculates the ratio of correctly predicted positive instances among all actual positive instances. It is calculated by taking the sum of true positive and false negative and then dividing the true positive with the calculated sum, as given in the formula below.

Recall= TP / TP + FN

3.8.5 Specificity

An indicator of how well the algorithm can detect negative occurrences, complementing recall value by emphasizing true negative value.It is also known as true negative rate and is calculated by below given formula.

Specificity = TN / (TN +FP)

3.8.6 Confusion Matrix

Confusion matrix is used to evaluate the performance of a machine learning model. It is a matrix that show the total number of true positive (TP), true negatives (TN), false positive (FP) and false negative (FN). It summarizes the overall performance of classification model by computing predicted class labels and true class labels.

3.9 Summary

This chapter gives an overview of research methodology, elaborate data collection and preprocessing methods, other techniques and tools chosen to achieve the research objective.In order to give a comprehensive grasp of how the study was carried out to accomplish its goals, it provides a full analysis of the experimental techniques used.

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Overview

This chapter presents a comprehensive analysis of findings derived from proposed research model for automated brain tumor classification and detection. The two models standalone LSTM and hybrid model are analyzed. The chapter starts by showing the experimental results, the main findings, and discussion about improvements such as enhanced classification results, low false positive rate and and improved feature engineering through advance deep learning solutions. A thorough overview of previous research is presented at the end. This comparison discusses advancements in accuracy, detection rates, and overall performance by inspecting the recommended approach with commonly used techniques.

In AI, model validation is an important aspect in order to get insight reliability and effectiveness of model. A robust model generalize well on new unseen data. The dataset is commonly separated into training subset, used to learn and train the model by learning various patterns and updating the hyperparameters, and a testing subset that is employed to evaluate the model's prediction and validates its applicability in real world. To figure out how well the model classified MRI images into four categorizes glioma, meningioma, pituitary tumor, and no tumor its performance was thoroughly examined.The model is trained for 50 epochs and its performance is determined by various performance metrics such as F1 measure, accuracy, precision and recall.

4.2 Experimental Results

The findings of suggested LSTM and hybrid UNET+LSTM outlines in table 4.1. The learning accuracy of first model that is being developed is determined to be 89.22%, while its test accuracy is computed as 87.11%. The second hybrid model attained a training accuracy of 99.12%, and validation accuracy 98.22%. The summary of evaluation metrics for all four classes including precision,accuracy, recall, and F1-measure, obtained from the LSTM and UNET+LSTM models are given in table 4.2. Progression in training and validation accuracies along with the corresponding loss values pertaining to the number of epochs are shown in Figure 4.1 and 4.2.

Table 4.1: Classification accuracy of models

Model	**Training ACCU**	**Test-ACC**	**Train-Loss**	**Val-Loss**
LSTM (Model 1)	89.22 %	87.11%	0.7051	0.7722
2DUNET+LSTM (Model 2)	99.12 %	98.22 %	0.3051	0.4051

4.3 Accuracy

Figure 4.1 and 4.2 illustrates the training and validation accuracies of LSTM and hybrid model. Upward trend of accuracy graph for both the models across the chosen 50 epochs indicating a stable learning pattern. The LSTM model has a training accuracy of 0.89 and validation accuracy of 0.87, whereas the hybrid model achieve 0.95 and 0.97 training and validation accuracy, respectively.

To provide more visual clarity and comparison understanding of accuracies across each epochs, the validation and training accuracy graphs of both models are plotted on same graph. Figure 4.3 shows this comparative accuracy graph.

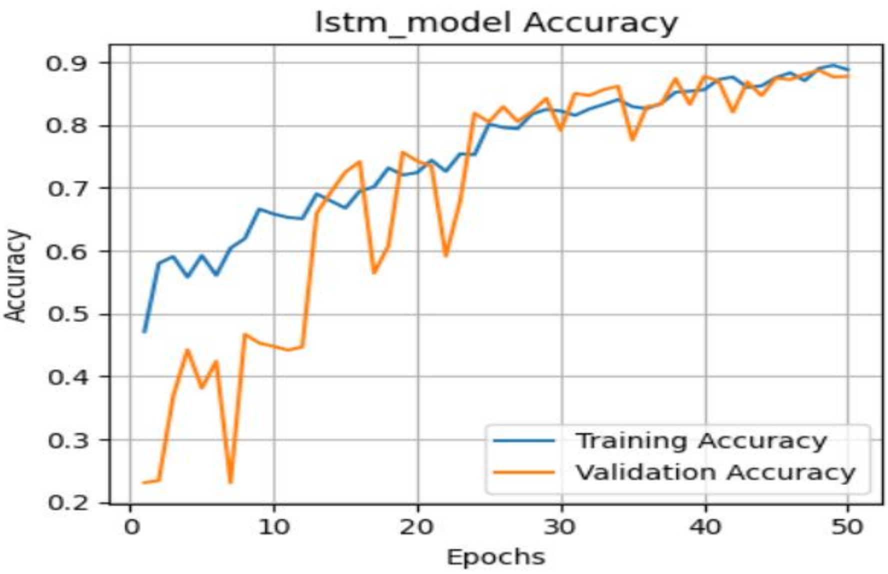

Figure 4.1: LSTM (Model 1) accuracy

Both models curve demonstrate uniform learning pattern, moreover during whole training process the hybrid model super pass than standalone LSTM model. It has been observed that the curve of hybrid model raises more sharply and stabilize at a higher value than that of LSTM.

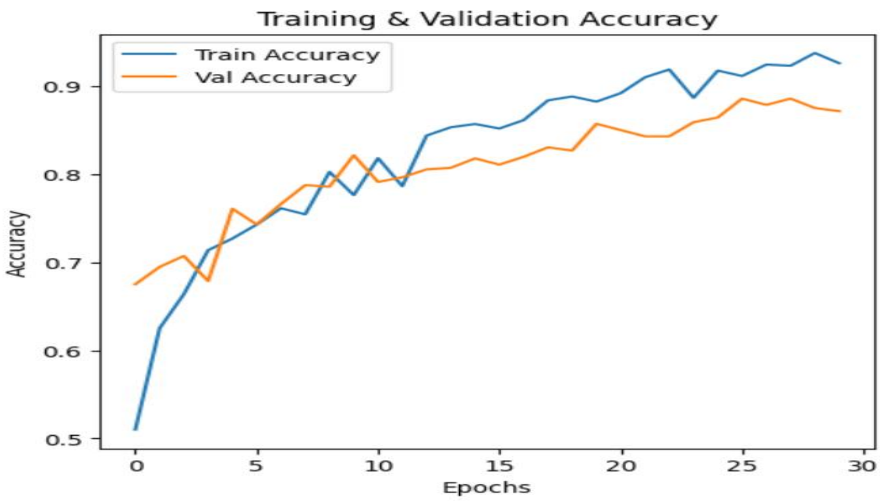

Figure 4.2: UNET+LSTM (Model 2) accuracy

The hybrid model represents the greater efficacy of integrating LSTM temporal learning capabilities with U-Net spatial feature extraction by achieving a validation accuracy of 0.95 and training accuracy of 0.95.

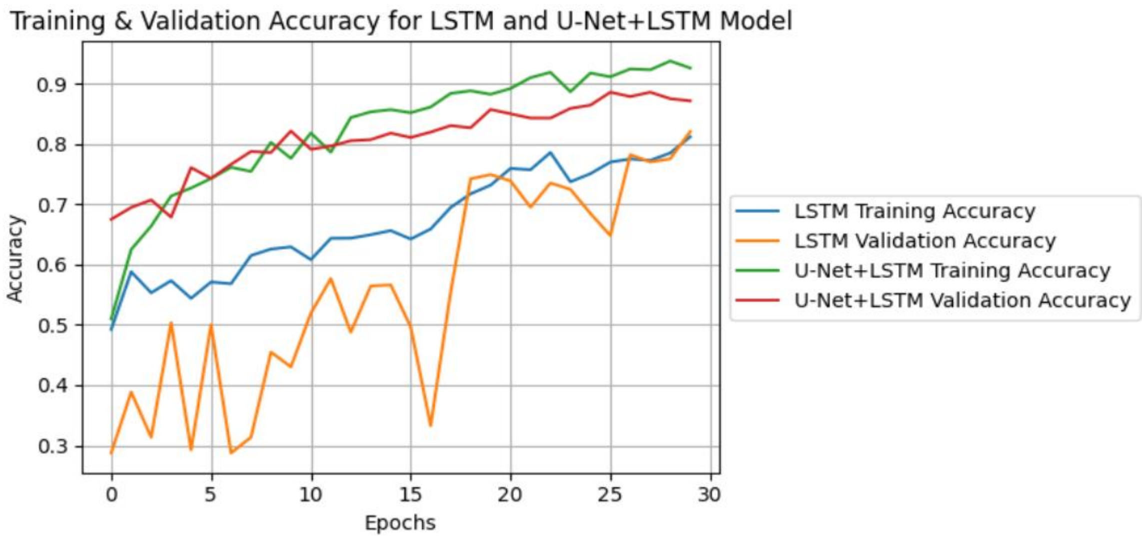

Figure 4.3: Training & validation accuracy of LSTM & (UNET+LSTM) over 30 epochs

4.4 Loss

The loss graph of proposed models demonstrates a significant decreasing trends and is plotted in below figures. LSTM starting loss value of 3.5 at very first epoch is then reduced to a value 0.03 by the 50th epoch portrayed in Figure 4.4, while the hybrid model value decreases from 11.6 to 8.0 by passing epochs shown in figure 1 and 2, accordingly.

In the early epochs from 1 to 10 both models showing high loss reduction. The LSTM loss value decreases more steeply than that of hybrid model, which relies on high level feature map extraction via UNET encoder. From epoch 11 to 25, there is more rapid decline in loss of both models, the hybrid model loss curve shown in Figure 4.5 perform more better and reduces loss at greater rate than LSTM.For the remaining epochs, both models start to plateau, indicating stability with only minor fluctuations.

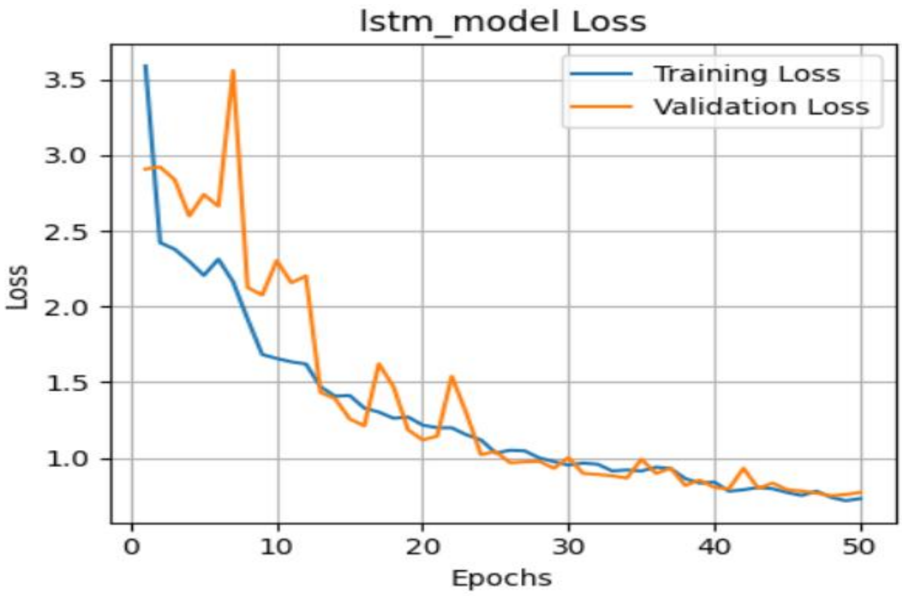

Figure 4.4: LSTM model loss

This loss decline reflects both the model's effective architecture and high quality reliable training data. The curve shows steady parameter optimization, gradually leading to point of minimal loss, proving how effectively the model has been optimized and learned. Figure 4.6 plot the loss of both models on same graph, which clearly illustrates the improved generalization and optimization of hybrid model upon LSTM model across all epochs.

Figure 4.5: UNET+LSTM model loss

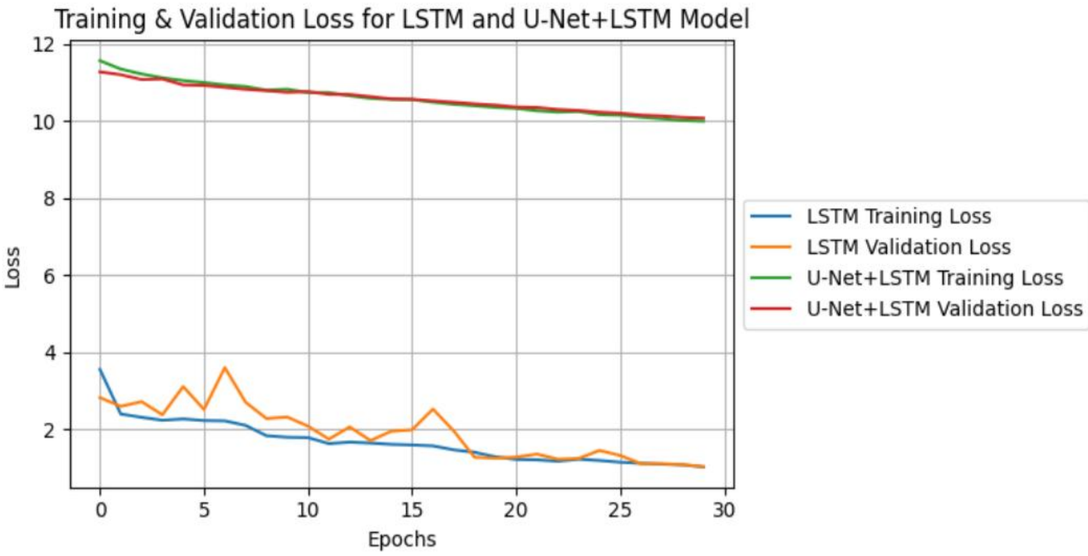

Figure 4.6: Training & validation loss analysis of LSTM & UNET+LSTM over 30 epochs

4.5 Class wise Classification Report

The classification report details the summary of performance measure parameters i.e accuracy, precision, recall, F1-score, and support. The test accuracy of both the models illustrated in table 4.2. It is crucial for evaluating model's performance in case of imbalanced dateset, as it must ensures that all classes are contributed equally, therefore helps in mitigating the biasing issue toward majority classes.

4.5.1 Precision

Table 4.2 illustrates the precision value of 0.87 and 0.98 for glioma tumor indicates that corresponding 87% and 98% of glioma predicted by the two models are correct and actually belonging to glioma class. The 0.78 and 0.96 values for meningioma by both models determines 78% and 96% of meningioma predicted instances by each model are correct. Where as 0.94 and 0.97 values against pituitary tumor shows 94 and 97% corrected predictions for this class. Similarly 0.88 and 0.95 no tumor class prediction reflects 88% and 95% of instances predicted as No tumor are actually no tumor. Precision value for all the classes is approximately >=90% of model 1 and 98% of model 2 therefore the model 2 seems to be more reliable having exceptional classification performance in brain tumor classification. Pituitary tumor class is written in bold as it has higher precision value i.e 97%. The macro average simply computes the average of all precision, while weighted average is the weighted mean of precision values.

4.5.2 Recall

A 80% and 96% of recall value for glioma tumor in table 4.2 means that LSTM correctly classified 80% and HM correctly classified 96% of glioma instances, while misclassified 8 and 4 instances respectively. In case of false negative model misclassifies a true positive instance (a tumor) as negative instance (no tumor). A model with high recall has low false negative value. Among all the true meningioma cases 69% and 97% are predicted correctly by model 1 and 2, showing a good recall value by model 2. The pituitary tumor are accurately predicted as 97 % and 99 % and missed by 3% and 1%.

Both models truly determined 96% of all actual no tumor cases. By making comparative evaluation of both models class wise report, model 2 has more better outcomes to categorize tumor and no tumor instances across all 4 four classes, making it more appropriate and applicable for healthcare solutions.

4.5.3 F1 Measure

By combining the precision and recall, f1 provides a balance measure. Model1 has f1 score of 0.84, 0.73, 0.95, & 0.93, while model 2 scores 0.92, 0.95, 0.87, & 0.90 for respective classes of meningioma, glioma, pituitary and no tumor. The overall F1 score of both models in contrast shows that the second model is more robust and reliable in its results. No tumor has the highest f1 score among all other types therefore it is noticeable that the model 2 is mostly often correct in differentiating no tumor class instances.

4.5.4 Support

The true number of instances for each class in test set calculated in support value. The total support value of model 2 is 1,311, whereas its accuracy is measured as 99%. Therefore out of 1,311 samples , there are 1,297 correct predictions showing 99% accuracy.

Table 4.2: Class wise classification report of LSTM and HM on test set

Class	**LSTM**			
	Precision	Recall	F1 Score	Support
Glioma_tumor	0.87	0.80	0.84	300
Meningioma	0.78	0.69	0.73	306
No_tumor	0.88	0.99	0.93	405
Pituitary_tumor	0.94	0.97	0.95	300
Accuracy	-	-	0.87	1311
Macro avg	0.87	0.86	0.86	1311
Weighted avg	0.87	0.87	0.87	1311
	HM (UNET + LSTM)			
	Precision	Recall	F1 Score	Support
Glioma_tumor	0.98	0.96	0.92	300
Meningioma	0.96	0.97	0.95	306
Pituitary	**0.97**	**0.99**	**0.87**	**405**
No_tumor	0.95	0.97	0.90	300
Accuracy	-	-	0.98	1311
Macro avg	0.87	0.86	0.99	1311
Glioma_tumor	0.98	0.96	0.92	300

4.6 Receiver Operating Characteristic Curve (ROC)

The ROC curve graphically show the model's trade- off to distinct between classes. Figure 4.9 illustrates the receiver operating characteristic (ROC) curves of both the models to determine how well the various tumor classes were classified . The ROC curve showcase the graphical presentation of sensitivity (true positive) versus specificity (false positive rate) at different points. The resultant curves, where the models achieved highest performance by attaining highest sensitivity and low specificity is noticeable for both the models.The shape of curve depicts the efficacy of model, a model with high true positive rate has sharp raising curve toward top left corner.

4.7 Confusion Matrix

In AI domain, confusion matrix is that matrix which comprises of different rows and columns for each class, it is used to visualize the overall model tumor type classification performance. Each row represents the true (actual) value of instances and each column indicates the predicted value of instance. The actual and predicted class labels are compared to investigate that there are how many correct and incorrect classified samples by the model. An ideal model have low misclassification rate, showing zero values at off-diagonals of confusion matrix. In medical research it is crucial to have lower Type I error (false positive) and Type II error (false negative) rate that can lead to severe health consequences of misdiagnosis and delayed medical intervention. The experimental data of Type I and Type 2 error rates and its impact overall classification performance of model is illustrated in Figure 4.7 and 4.8.

According to the results shown in confusion matrices, the HM shows higher number of correct predictions for four tumor labels. Conversely, LSTM exhibits relatively poor outcomes. The false positive rate of both models is calculated as under.

Calculation of False Positive Rate of LSTM for No Tumor Class:

True Negative=241+ 53+3+30+210+ 16+ 01+06+ 292 = 852

False Positive= 01+50+ 03= 54

False Positive rate = *False Positive / (False Positive + True Negative)*

= 54 / (54 + 852) = 54/ 906 = 0.0596

Thus the False Positive Rate is 0.0596 (i.e 5.96 %) means LSTM model accurately predicts 94.64% of non tumor cases.

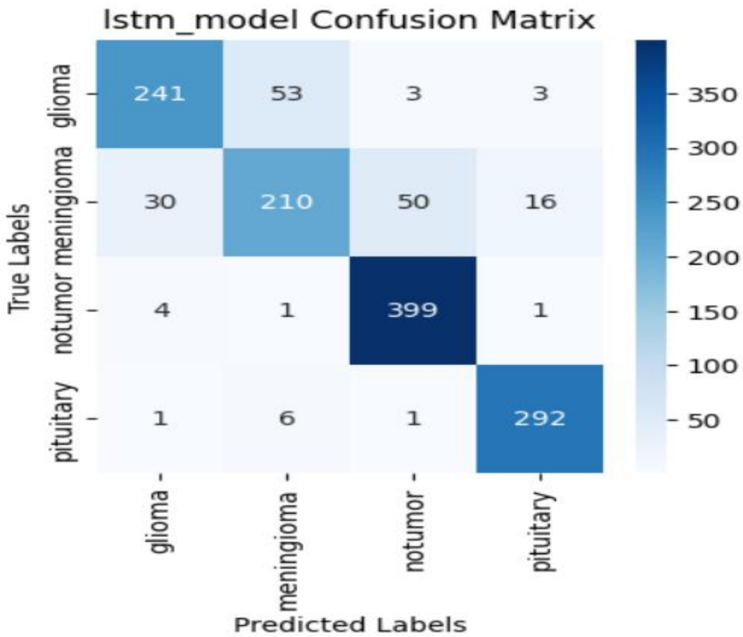

Figure 4.7: Confusion matrix indicating TP, TN, FP, FN of LSTM model

Calculation of False Positive Rate of HM (2D UNET+LSTM) for No Tumor Class:

True Negative = 285 + 1 + 3 + 0+ 230 + 0+ 1+ 0 +292 = 812

False Positive = 0+5+1 = 06

False Positive Rate = *False Positive / (False Positive + True Negative)*

= 06 / (06 + 812) = 0.00734

Thus the False Positive Rate is 0.00734 (i.e 0.734%) means Hybrid model accurately predicts almost 100% of non tumor cases.

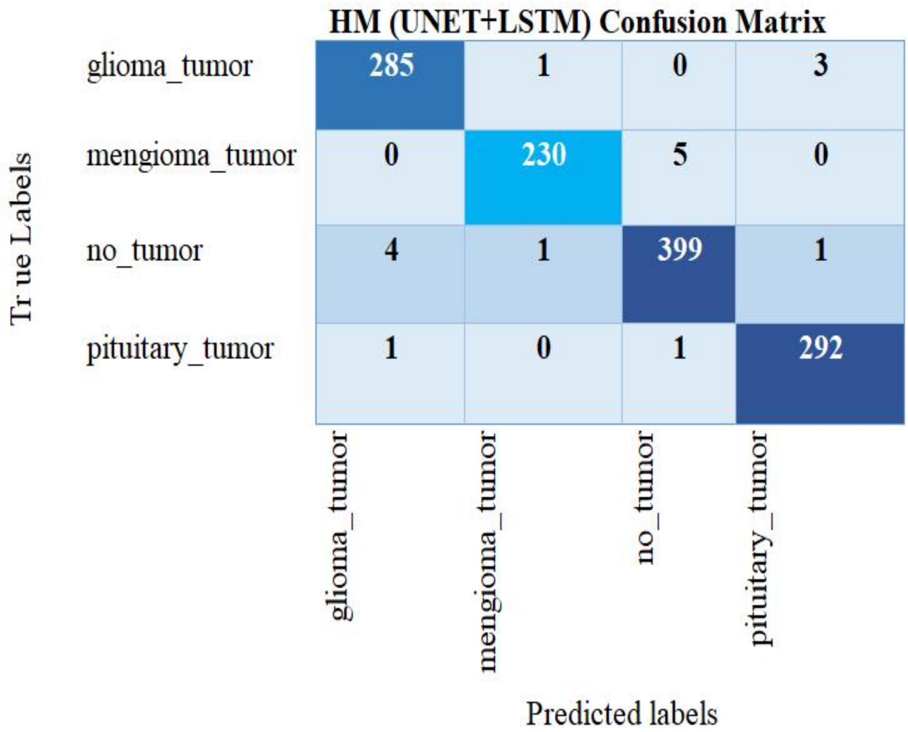

Figure 4.8: Confusion matrix indicating TP, TN, FP, FN of HM (UNET+LSTM) model

4.8 Comparison with Existing Studies

The research presents comparative analysis among developed hybrid framework and previously benchmark techniques available for medical imaging tumor analysis. The analysis report the significant improvement of suggested model over many machine learning and deep learning algorithms. Table 4.3 below access various models naming Model 1 to Model 5 in term of their accuracy , precision, recall and f1 score.

i. *Model 1 (Mallampati, 2023):* have the same value across all the metrics i.e 71 %, which highlights that the results are relatively low with respect to current approach.
ii. *Model 2 (Rajeev , 2023):* shows much better outcomes i.e 97.74% accuracy, relatively near to other values of 97.77% precision, 97.83% recall and 97.80% f1 measure.
iii. *Model 3 (Mahjoubi, 2023):* demonstrated 95.44% accuracy and stable values of about 95% for other metrics, thus have enhanced classification accuracy.
iv. *Model 4 (Standalone LSTM):* LSTM is used for feature extraction and then labeling of tumor type, this technique attained 88.21% accuracy, 82.3% precision , 82.9% and 82.2%

recall and f1 score respectively. The model most often misclassified and have relatively low performance.

v. *Model 5 (HM : 2D UNET+LSTM):* have the highest values across all metrics written in bold, with accuracy 99.12%, precision of 99.3%, recall of 98.2%, and an F1-score of 97.5%. The empirical results indicates how the proposed hybrid framework improves model classification and generalization.

Table 4.3: Overall performance comparison of existing approaches & proposed study

Model	Author Name	Accuracy	Precision	Recall	F1 Score
Model 1	Mallampati [24], 2023	71.1%	71%	71%	71%
Model 2	Rajeev [61],2023	97.94%	97.77%	97.83%	97.80%
Model 3	Mahjoubi[23], 2023	95.44%	95.82%.	95%	95.36%
Model 4	LSTM	88.21%	8.23%	82.9%	82.2%
Model 5	**Proposed HM** **UNET + LSTM**	**99.12 %**	**99.3%**	**98.2%**	**97.5%**

4.9 Discussions

Bukhari et al.,2021 [27] conducted detecting and partitioning of tumor region i.e segmentation by using E1D3 U-Net, an enhancement to 3D U-Net architecture. Their suggested E1D3 UNET model has one encoder and three decoders developed using python libraries and run on GPU.The implemented design generates the segmentation results from the feature map generated by encoder part of model. The highest accuracy results achieved was 91% for hold out and 5 fold cross validation methods. Nonetheless, our suggested Hybrid model leads the best accuracy than recorded in aforementioned research (91.0%). The model proposed in this research took longer time to run due to large number of convolutional, max pooling, batch normalization and other layers , which justifies its best accuracy. The other factors including datasets, network chosen, the defined layers to improve generalization, layers defined to overcome class imbalances issue all these contributes to longer execution time. It is notifiable that complex network need longer time to learn intricate patterns than training shallower deep learning models.

In another research Support Vector Machine (SVM) classifier and Densenet201 were applied for labeling tumor classes.CNN architecture is applied by including convolutional layer, pooling layer, batch normalization and Relu layers. Then regularization techniques drop out and batch normalization are utilized to avoid the problem of overfitting and improving model generalization. Convolutional layers having multiple trainable weights used to learn various spatial feature and high level features from MRI scans. Model trained through back-propagation mechanism by progressively resetting values of weights for achieving the better outcomes. Lastly, fully connected layer transforms two dimensional array output to one dimensional array and softmax classifier used lastly to classifies the tumor type. The framework depicted an accuracy of 98% and 99% with Brats 2018 and 2019 datasets respectively [37]. But the author reported to still face major challenges i.e it eliminates the important feature to learn and also takes longer execution time due to fusion of various classifiers. How ever our proposed LSTM and hybrid model achieved an accuracy of 89.22 and 99.12 respectively. We have applied multiple convolutional layers in both models along with batch normalization, max polling and relu layers with a large dataset, the proposed model takes longer execution time but learn all the high level and low level features using encoder of UNET architecture with enhanced classification accuracy. The model is implemented on Google Colab with GPU runtime therefore leveraging the benefit of lower cost and hardware complexity. Other studies in comparison adopted network with small datasets and less number of layers.

While comparing both the models implemented in this research, the hybrid model with and accuracy score of 99.12 outperform than standalone LSTM. However the LSTM model is more simpler and have faster convergence than hybrid model. Both models are executed over 50 epochs, each epoch is executed for 100 steps, the suggested hybrid model takes more execution time to run each epoch than LSTM model. Since the hybrid model unifies UNET feature learning capabilities and LSTM handling temporal dependencies in MRI sequence dataset it takes longer time while achieves best accuracy, recall,precision and f1 measure.

Table 4.4: Comparative analysis of proposed and existing works

Author Name/ Year	**Classifier Type**	**Dataset**	**Technical Platform**	**ACCU**	**k-Fold cross-validation / data division**
Pranitha (2024), [59]	EL-DC LSTM + UNET + EPO's optimization	BraTs 2020	Python Platform	98%	70 : 30% split ratio, 80% & 20 % splitting percentage
Saeedi 2023, [12]	2D CNN & auto-encoder network	Kaggle dataset	Keras, Tensor flow, Google Colab, Python language, GPU runtime	96.47% & 95.63%	90% training data, 10% testing data
Mallampati 2023, [24]	Hybrid model (KNN+GBC), 2D UNET & 3D UNET	RSNA-MICCAI dataset of Kaggle	Jupyter Notebook, Python 3.9, Pandas 1.4.4, sklearn 1.0.2, and Tensorflow	64% and 71% ACCU	90% training and 10% for testing
Bukhari, 2021, [27]	E1D3 UNET (with three Decoders)	BRATS 2018 & 2021	NumPy, NiBabel, PyTorch & TorchIO, GPU	91.0	90% data in training, 10% in validation in brats 2018), Hold-out & 5-fold cross-validation
Sharif 2021, [37]	Densenet201 , SVM	BRATS 2018 & 2019	MATLAB2020, g Core i7 Desktop Computer	95	50 % datset for training & 50 % for testing with 10-Fold cross-validations
Proposed Approachs	LSTM , UNET + LSTM	Kaggle (MRI) dataset: four classes	Python3, Sklean 1.0.2, Tensorflow, Google Colab	89.21 % , 99.12 %	80% training datsset, 20% testing dataset

In [12], researchers developed two deep learning models 2D CNN and auto-encoder network with eight convolutional and four pooling layer in 2D CNN. Padding is applied to manage edges and softmax activation is used for classification. Different learning rate of 0.01, 0.001 and 0.0001are used with adam optimizer function. Batch size 16 is chosen and model is trained for 100 epochs. The auto encoder uses two consecutive convoultional layers with 128 and 64 kernel size. The network learned various patterns for 100 epochs each with a batch size of 16. The python language with keras and tensorflow back-end technologies are utilized to develop models. Their 2D CNN achieved 96.47% accuracy and 95.63% accuracy results demonstrated by auto-encoder. These results are not optimal as analyzed with the outcomes obtained in the current research.

A hybrid model was proposed in other research to detect brain tumor. 2D and 3D UNET segmentation features utilized to train the model and to improve its performance. This model was implemented on Python 3.9, Pandas 1.4.4, sklearn 1.0.2, and with Tensorflow backend setup. Further to enhance accuracy the researcher integrated K-Nearest Neighbors (KNN) and Gradient Boosting Classifier (GBC) through soft voting mechanism. The model attained 64% accuracy for segmentation features of 2D UNET and 71% accuracy for 3D-UNet segmentation features[24]. It is notified that feature map generated by 3D UNET yield more robust learning as compared to 2D UNET feature map. They achieved the best outcomes of 71% accuracy.

Like the deep learning models used in this research, Pranitha (2024) achieved 98% accuracy with EL-DCLSTM model. . They performed preprocessing of images by resizing, cropping undesired areas, filtering and normalizing. Various layer, like convolutional layer, pooling layer, LSTM layer, fully connected layer, and output layer are chosen respectively. The advance UNET architecture most often used for biomedical image segmentation, utilized to delineate the region of interest. The segmentation divides an image into different segments or regions. Using EPO's optimization with UNET architecture proposed model outperform the segmentation through continuous upgradation of bias and weights parameter. The fine tuned ResNet model employed for feature engineering and lastly extracted features fed into EL-DCLSTM for classification task. The highest accuracy obtained by this approach is 98%. In this study bias field correction is applied to remove intensity in homogeneity in MRI images, similar to this research the research researcher preprocessed the images through Gaussian filters. Data augmentation help to artificially create diverse images in training data. Notably, in this research the author augment the training data by rotating, flipping, shearing and scaling the MRI images like wise the proposed method does in current research. The test accuracy of proposed hybrid model in this research found to be more significant than this approach; nevertheless this approach have more high level features by down sampling through encoder and then passing the reduced-resolution image to bottleneck layer for high level feature extraction.

Thus, the suggested Hybrid model outperform the previously used approaches because it balances model complexity and performance effectively. It learns directly from data in an end-to-end fashion. By carefully modifying the model architecture via these cutting-edge strategies we achieved the goal to achieve significant performance improvements.The model's capabilities have been substantially improved by the dropout regularization, early halting, and learning rate scheduler adjustments . Consequently, the model's generality and accuracy in brain tumor classification have improved. A more robust and dependable system that can handle various and invisible data better has resulted from these improvements. This development has broader consequences for the deep learning community in addition to enhancing the success rate of our customized model.

4.10 Summary

This chapter presented the model outcomes in term of accuracy, loss, and class wise classification analysis across all four classes of tumor. The confusion matrix, ROC curve and comparative analysis with existing methods is illustrated to showcase the efficacy of model. Quantitative results reveal that using hybrid approach is proven to be more effective across all evaluation metrics indicating more efficient and robust model design. Overall, the insights affirm the robustness of the proposed hybrid approach and its potential to improve automated brain tumor identification and labeling.

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 Conclusion

The primary motivating factor of this study was the dire need of precise and automatic approach to assist in detection of brain tumor. Timely intervention is significant for patient survivals and outcomes, manual detection is often inaccurate and time taking due to intricate pattern of brain tissues. This recognized the requirement of reliable and robust diagnosis system. The research put forth a state-of-art deep learning hybrid architecture for automatic brain tumor detection and classification into four primary categorizes- glioma, meningioma, pituitary tumor, and no tumor. To mitigate the class imbalance issue and reduce overfitting problem, initially the training dataset is augmented and pre-processed. The UNET architecture was then chosen for spatial feature extraction from MRI images. Then LSTM is applied to leverage the features for tumor classification and learning temporal dependencies. To speed up convergence the learning rate is carefully adjusted during training, the model checkpoint is observed to preserve model weight at best results, plotting loss curves, and early stopping tactics have been implemented. The model applied to MRI brain tumor dataset comprises of 5,712 grayscale images of four tumor classes. The model obtained a remarkable accuracy of 99% on kaggle MRI dataset. Accuracy was comprehensively evaluated using a number of key parameters, including precision, recall, specificity, and F1 score, which showed how well the model performed. These results collectively demonstrate the effectiveness of the proposed model in accurately classifying brain tumors, its efficacy in its operating speed as well as its robustness in reducing false negative and false positive predictions. In subsequent research, the goal is to encompass various MRI modalities to capture wider spectrum of MRI tumor images, employing pre-trained model, focusing on large datasets and real time deployment for various clinical use.

5.2 Future Work

In future research, considering the significance of timely and precise diagnosis of brain tumor without latency, there is need to develop robust deep learning model for brain tumor detection with greater simplicity and less execution time. Additionally, further research could investigate the integration of multi modal imaging data, such as CT, PET, or MRI scans. The performance of the U-Net in tumor localization could be further improved by using expert-annotated segmentation masks as ground truth labels. Furthermore, the research can be advanced by accessing model's performance on more comprehensive and complex datasets, like 3D MRI, featuring a wider spectrum of tumor types, sizes, and locations. Optimizing the model's architecture to lower computational load and enable implementation in real-time clinical settings is another crucial avenue.

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