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BRAIN TUMOR DETECTION USING A HYBRID CNN–GOOGLENET–LSTM MODEL ON MRI IMAGES

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ABSTRACT

Brain tumor detection is a critical task in medical diagnosis that requires high accuracy and reliability. Magnetic Resonance Imaging (MRI) is widely used for identifying brain tumors, but manual analysis is time-consuming and prone to human error. This paper proposes a hybrid deep learning model that integrates Convolutional Neural Networks (CNN), GoogLeNet, and Long Short-Term Memory (LSTM) networks for automated brain tumor detection. The proposed system utilizes GoogLeNet for efficient spatial feature extraction from MRI images, while LSTM captures sequential dependencies across multiple MRI slices. This combination enables the model to analyze both spatial and temporal information, improving classification accuracy. The system includes preprocessing techniques such as image normalization, resizing, and noise reduction, followed by feature extraction, sequence modeling, and classification using a softmax layer. The model is implemented using deep learning frameworks and evaluated using standard performance metrics such as accuracy, sensitivity, and specificity. The results indicate that the hybrid CNN–GoogLeNet–LSTM model provides improved performance compared to traditional CNN-based approaches. This system can assist radiologists in faster and more accurate diagnosis.

Index Terms — Brain tumor detection, Convolutional Neural Network (CNN), GoogLeNet, LSTM, MRI classification, Hybrid deep learning, Medical image analysis.

I. INTRODUCTION

Brain tumors are among the most critical and life-threatening neurological disorders, significantly affecting human health and survival rates. Early and accurate detection of brain tumors is essential for effective treatment planning and improving patient outcomes. Magnetic Resonance Imaging (MRI) is widely used for brain tumor diagnosis due to its ability to provide high-resolution images of brain tissues without exposing patients to harmful radiation.

Despite its advantages, manual analysis of MRI scans is a time-consuming and complex process that depends heavily on the expertise of radiologists. Variations in tumor shape, size, intensity, and location make accurate diagnosis challenging and may lead to misinterpretation or delayed detection. With the increasing volume of medical imaging data, there is a growing need for automated and reliable diagnostic systems.

Recent advancements in deep learning have significantly improved the performance of medical image analysis. Convolutional Neural Networks (CNNs) have demonstrated strong capability in extracting spatial features from MRI images. However, CNN-based models primarily focus on individual image slices and fail to capture sequential dependencies across multiple MRI slices of the same patient.

To overcome this limitation, hybrid deep learning approaches have been introduced by integrating CNNs with Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks. LSTM models are effective in learning temporal relationships, enabling better understanding of tumor progression across MRI slices. Additionally, advanced architectures such as GoogLeNet enhance feature extraction through multi-scale analysis using inception modules.

In this paper, a hybrid deep learning model combining CNN, GoogLeNet, and LSTM is proposed for brain tumor detection using MRI images. The proposed system integrates spatial feature extraction and sequential learning to improve classification accuracy and robustness. The model is designed to assist radiologists by providing faster and more reliable diagnostic results.

The main contributions of this work include:

- Development of a hybrid CNN–GoogLeNet–LSTM architecture for tumor detection
- Integration of spatial and temporal feature learning
- Implementation of an automated system for MRI-based classification

II. BACKGROUND STUDY

A. Magnetic Resonance Imaging (MRI) for Brain Tumor Detection

Magnetic Resonance Imaging (MRI) is a non-invasive imaging technique used to visualize soft tissues within the human brain. It provides excellent contrast between healthy tissue and abnormal tumor regions. MRI is preferred because it does not involve ionizing radiation and offers multiple imaging modalities, each highlighting different anatomical structures.

The commonly used MRI modalities are:

- T1-weighted MRI: Shows clear anatomical structure; tumors appear darker.
- T2-weighted MRI: Highlights fluid and edema; tumors appear brighter.
- FLAIR (Fluid Attenuated Inversion Recovery): Suppresses fluid and enhances the visibility of lesions near cerebrospinal fluid regions.
- T1CE (T1 Contrast Enhanced): Highlights tumor boundaries using contrast agents.

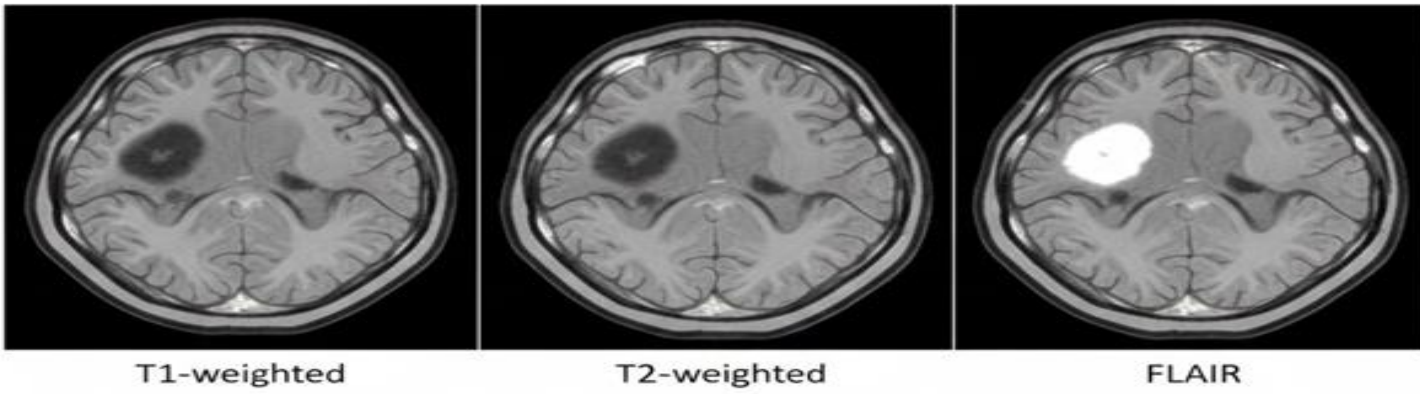

Figure 1. Sample MRI images (T1, T2, FLAIR).

B. Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) are deep learning models designed to automatically extract spatial features from images. They learn hierarchical patterns such as edges, textures, and shapes, making them highly effective for medical image classification tasks.

Key Components of CNN:

- **Convolution Layers:** Perform feature extraction using learnable filters.
- **Pooling Layers:** Reduce spatial dimensions for computational efficiency.
- **Activation Functions (ReLU):** Introduce non-linearity for better learning.
- **Fully Connected Layers:** Perform final classification.

CNNs excel in spatial learning but are limited in understanding sequential patterns across multiple MRI slices.

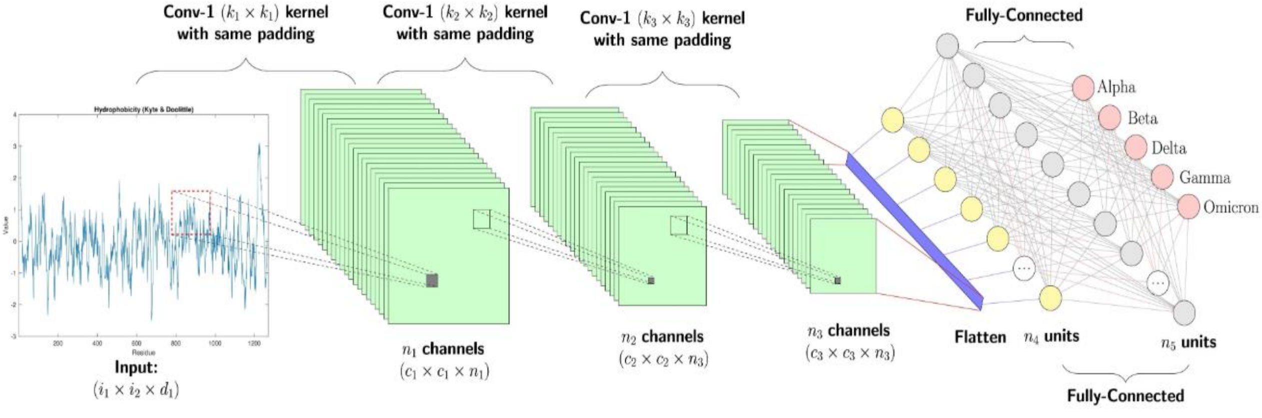

Figure 2. Basic architecture of a Convolutional Neural Network.

C. GoogLeNet Architecture

GoogLeNet is a deep CNN architecture based on **Inception modules**, introduced to improve multi-scale feature extraction while reducing computational cost. Unlike traditional CNNs that use a single filter size at each layer, GoogLeNet performs parallel convolution operations using multiple filter sizes (1×1, 3×3, 5×5).

Advantages of GoogLeNet:

- Efficient multi-scale feature learning
- Lower number of parameters
- Greater depth with reduced computation
- Better generalization on medical datasets

The inception module merges the outputs of parallel convolutions, capturing tumor features of different sizes and shapes.

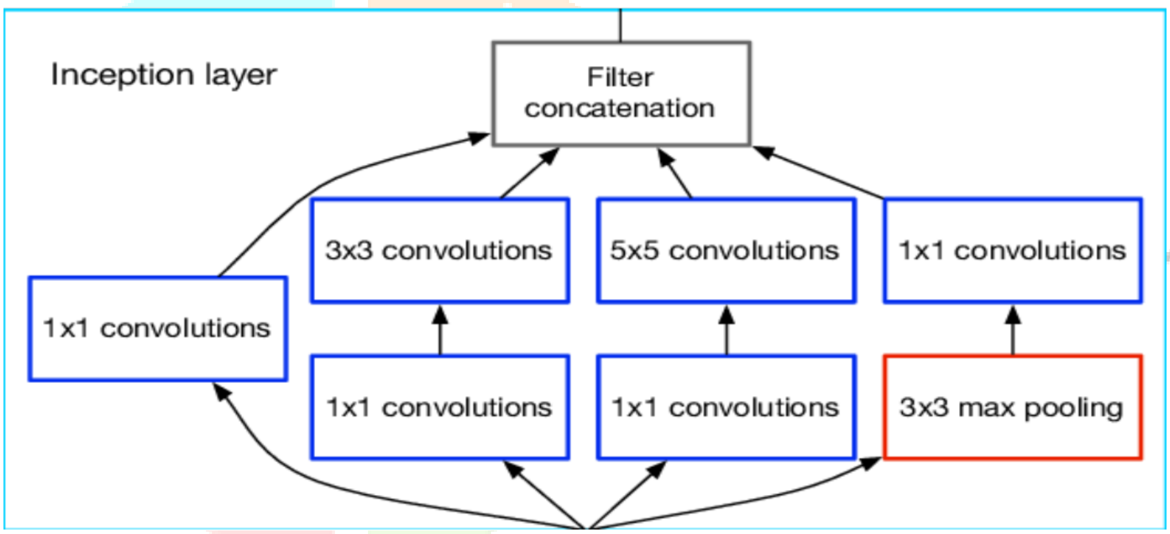

Figure 3. Inception module used in GoogLeNet.

D. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) networks are a special class of Recurrent Neural Networks (RNNs) designed to learn long-term temporal dependencies. LSTM is particularly useful in MRI analysis because multiple slices of a brain MRI can be treated as a sequential dataset.

Main Components of LSTM:

- **Forget Gate:** Discards irrelevant information.
- **Input Gate:** Selects new information to store.
- **Output Gate:** Determines final output for next time step.

LSTM models are effective for capturing temporal relationships that CNNs alone cannot learn.

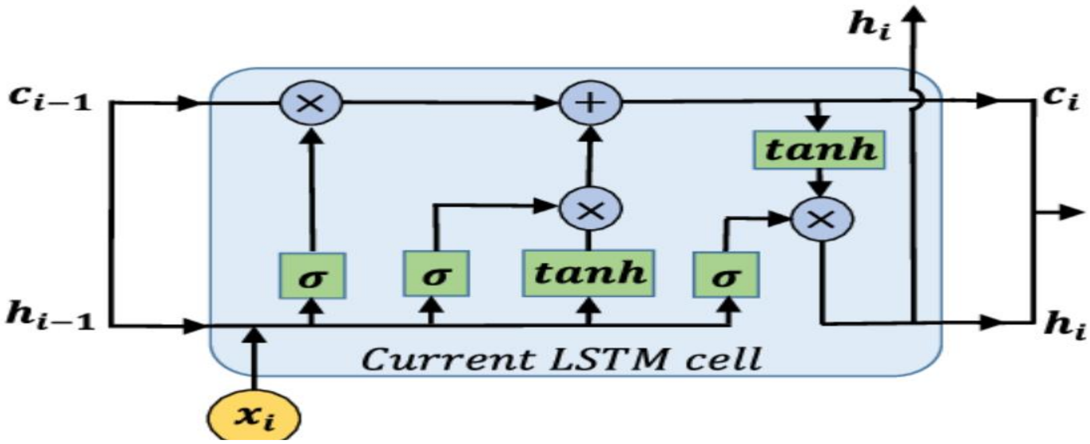

Figure 4. Internal structure of an LSTM cell.

E. Hybrid CNN–GoogLeNet–LSTM Architecture

A hybrid deep learning model integrates the strengths of all three architectures:

- **CNN:** Captures spatial features.
- **GoogLeNet:** Extracts multi-scale, deeper features.
- **LSTM:** Learns sequential patterns across MRI slices.

Why Hybrid Models Are Superior:

1. Capture spatial + multi-scale + temporal information
2. Reduce classification errors
3. Improve model robustness
4. Provide higher accuracy compared to single networks

These hybrid models are increasingly used in brain tumor detection because they combine complementary strengths of multiple deep learning architectures.

III. LITERATURE SURVEY

Recent advancements in deep learning have significantly improved brain tumor detection using MRI images. Convolutional Neural Networks (CNNs) have been widely adopted due to their strong ability to extract spatial features such as edges, textures, and tumor boundaries. Several studies report high classification accuracy using CNN-based architectures; however, these models process MRI slices independently and fail to capture relationships across consecutive slices.

To overcome this limitation, hybrid models integrating CNN with Long Short-Term Memory (LSTM) networks have been proposed. LSTM networks enable sequential learning by modeling temporal dependencies between MRI slices, leading to improved tumor detection performance. These approaches have demonstrated better results compared to standalone CNN models, especially in multi-slice analysis.

In addition, advanced architectures such as GoogLeNet have been introduced to enhance feature extraction through inception modules, allowing multi-scale analysis of MRI images. GoogLeNet-based models provide improved accuracy and computational efficiency compared to traditional CNN architectures.

Despite these developments, existing methods often lack a unified framework that combines spatial feature extraction, multi-scale analysis, and temporal sequence learning. This limitation motivates the proposed hybrid CNN–GoogLeNet–LSTM model, which aims to improve classification accuracy and robustness in brain tumor detection.

IV. PROPOSED METHODOLOGY

The proposed system presents a hybrid deep learning framework for brain tumor detection using MRI images by integrating Convolutional Neural Networks (CNN), GoogLeNet, and Long Short-Term Memory (LSTM) networks. The methodology is designed to combine spatial feature extraction, multi-scale analysis, and temporal sequence learning for improved classification performance.

The overall workflow of the system includes data preprocessing, feature extraction, sequence learning, and classification**.**

A. Overall Workflow of the Proposed System

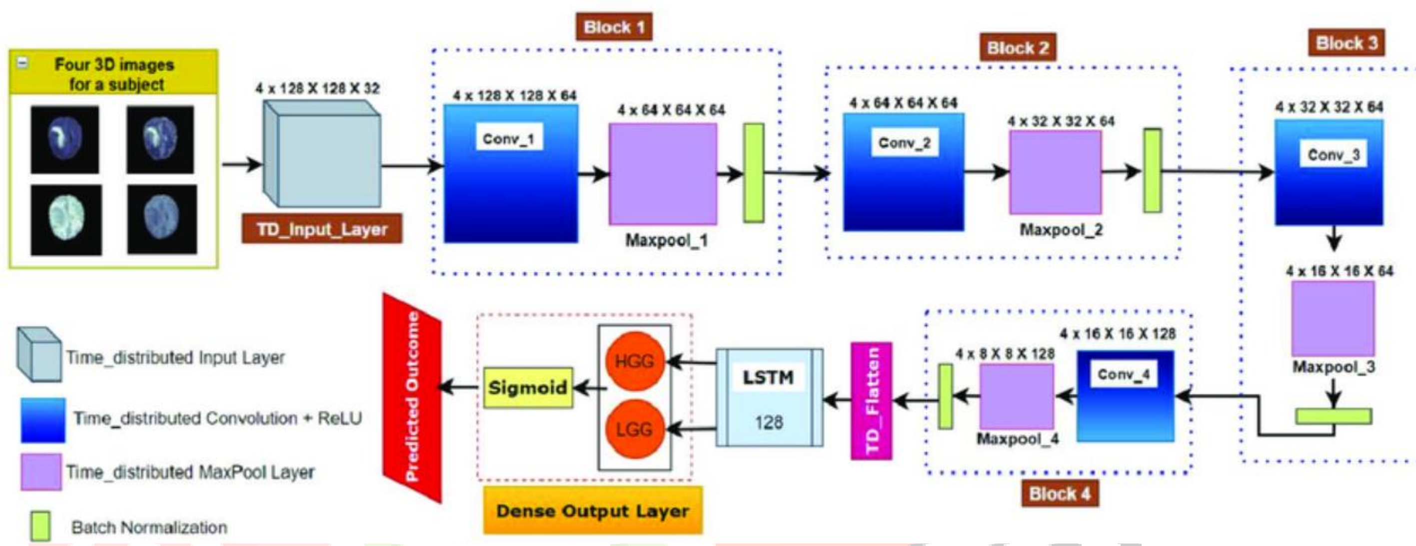

Figure 5: Overall workflow of the proposed brain tumor detection system

The system follows a structured pipeline:

1. MRI image input
2. Preprocessing
3. Feature extraction using GoogLeNet
4. Sequential learning using LSTM
5. Classification using softmax

B. Data Collection and Preprocessing

MRI brain images are collected from publicly available datasets such as BRATS and Kaggle MRI datasets. These datasets contain labeled images for tumor and non-tumor classes.

Preprocessing is a crucial step to improve data quality and model performance. The following operations are performed:

- **Resizing:** All images are resized to 224×224 pixels to match the input size of GoogLeNet.
- **Normalization:** Pixel values are scaled between 0 and 1 to stabilize training.
- **Noise Reduction:** Filters are applied to remove unwanted noise from MRI images.

- **Data Augmentation:** Techniques such as rotation, flipping, and zooming are used to increase dataset diversity and prevent overfitting.

C. Feature Extraction using GoogLeNet

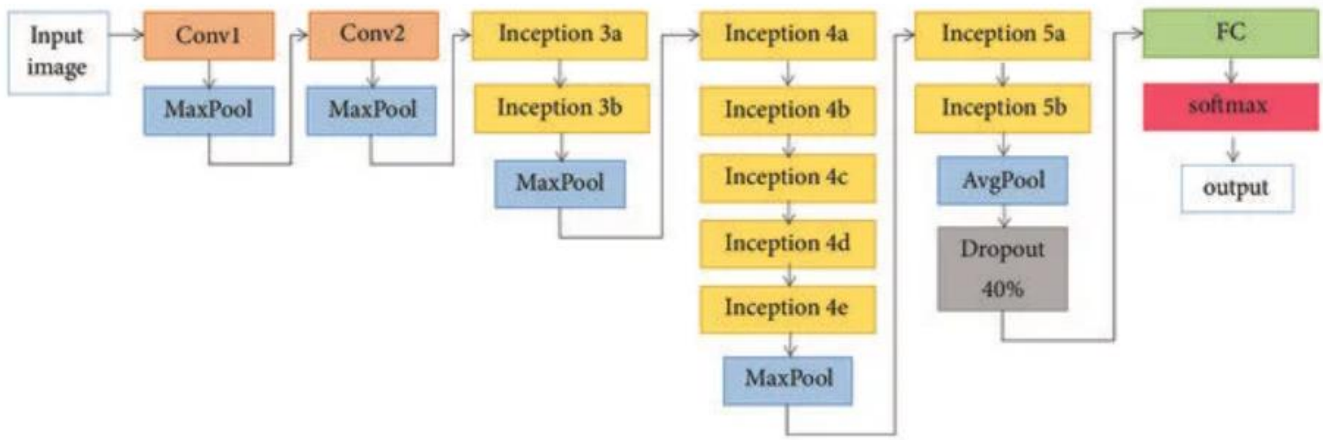

Figure 6: GoogLeNet architecture with inception modules for feature extraction

GoogLeNet is used as the primary feature extraction component due to its ability to capture multi-scale features efficiently. It utilizes inception modules that perform parallel convolution operations with different filter sizes (1×1, 3×3, 5×5).

This allows the model to:

- Capture fine and coarse tumor features
- Reduce computational complexity
- Improve generalization performance

The output of GoogLeNet is a set of high-level feature vectors representing MRI image characteristics.

D. Sequential Learning using LSTM

The extracted feature vectors are arranged into sequences and passed into the LSTM network. LSTM is capable of learning long-term dependencies using memory cells and gating mechanisms.

Key components of LSTM:

- Forget Gate: Removes irrelevant information
- Input Gate: Updates important features
- Output Gate: Produces final sequence output

This step enables the system to:

- Understand tumor progression across slices
- Capture temporal relationships
- Improve classification accuracy

E. Classification Layer

The output from the LSTM network is passed through fully connected (dense) layers followed by a softmax activation function.

The classifier:

- Assigns probability scores to each class
- Predicts tumor presence and type

F. Performance Evaluation

The performance of the proposed model is evaluated using standard metrics:

- **Accuracy:** Overall correctness of predictions
- **Sensitivity (Recall):** Ability to detect tumors correctly
- **Specificity:** Ability to identify non-tumor cases
- **F1-Score:** Balance between precision and recall

These metrics ensure the reliability of the model in medical diagnosis.

V. SYSTEM ARCHITECTURE

The architecture of the proposed brain tumor detection system is designed as a hybrid deep learning pipeline that integrates preprocessing, feature extraction, sequential learning, and classification. The system combines the strengths of GoogLeNet and LSTM to effectively analyze MRI images and improve diagnostic accuracy.

A. Overall Architecture Diagram

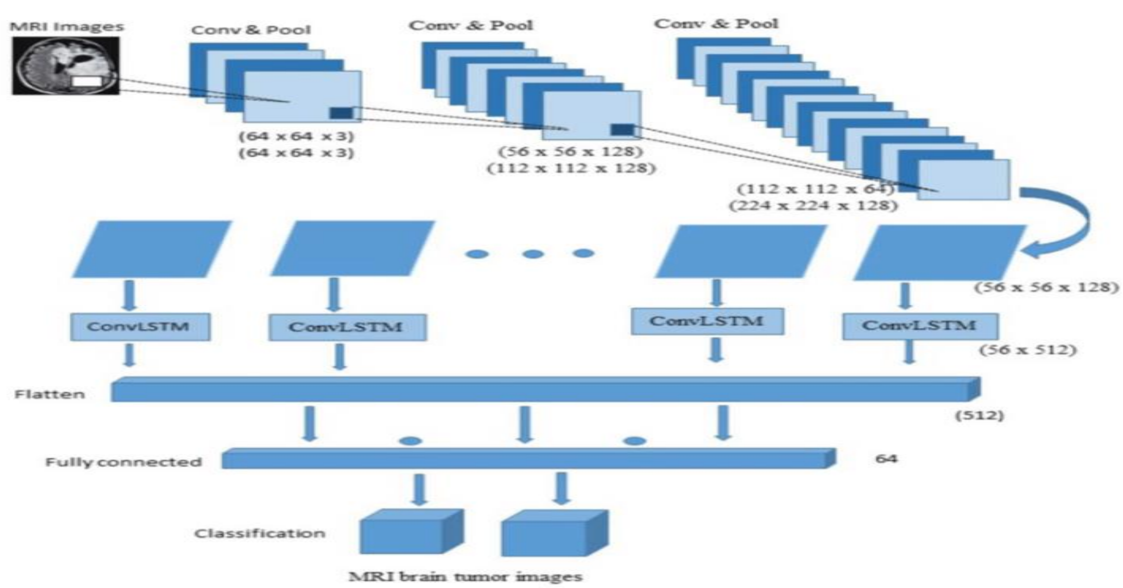

Figure 7: Proposed hybrid CNN–GoogLeNet–LSTM system architecture for brain tumor detection

B. Input Layer

The system takes MRI brain images as input, which may consist of single images or sequences of MRI slices. These images contain important structural and pathological information required for tumor detection.

C. Preprocessing Module

Before feeding the data into the model, preprocessing is performed to standardize the input images. This module includes:

- Resizing: All images are resized to 224×224 pixels
- Normalization: Pixel values are scaled to a fixed range
- Noise Reduction: Enhances image quality
- Data Augmentation: Improves model generalization

This step ensures uniformity and reduces variability in MRI datasets

D. Feature Extraction Module (GoogLeNet)

The preprocessed images are passed through the GoogLeNet model, which serves as the feature extraction layer. GoogLeNet uses inception modules to extract deep and multi-scale features.

Key advantages:

- Captures tumor features at different scales
- Reduces computational cost
- Improves classification performance

The output of this stage is a set of feature vectors representing spatial characteristics of MRI images.

E. Sequence Learning Module (LSTM)

The extracted feature vectors are arranged sequentially and fed into the LSTM network. This module is responsible for learning temporal relationships between consecutive MRI slices.

LSTM enhances the system by:

- Capturing tumor progression
- Learning contextual dependencies
- Improving prediction accuracy

F. Classification Module

The output from the LSTM layer is passed to fully connected layers followed by a softmax classifier.

The classifier:

- Assigns probability scores to different classes
- Predicts tumor type or presence

G. Output Layer

The final output of the system is the classification result, indicating whether a tumor is present and identifying the tumor category. The system may also provide confidence scores for predictions.

Architecture Flow Summary

The complete workflow of the system can be summarized as:

MRI Image → Preprocessing → GoogLeNet Feature Extraction → LSTM Sequence Learning → Fully Connected Layers → Softmax Classification → Output

VI. IMPLEMENTATION

The proposed brain tumor detection system is implemented using a hybrid deep learning approach that combines GoogLeNet and Long Short-Term Memory (LSTM) networks. The implementation is carried out using Python and deep learning frameworks such as TensorFlow and Keras.

A. System Environment

The development environment is set up to support both model training and deployment. The following tools and technologies are used:

- Programming Language: Python
- Deep Learning Frameworks: TensorFlow, Keras
- Libraries: NumPy, OpenCV, Matplotlib
- Web Framework: Flask
- Platform: Jupyter Notebook / VS Code

A virtual environment is created to manage dependencies and ensure smooth execution of the system.

B. Data Processing Pipeline

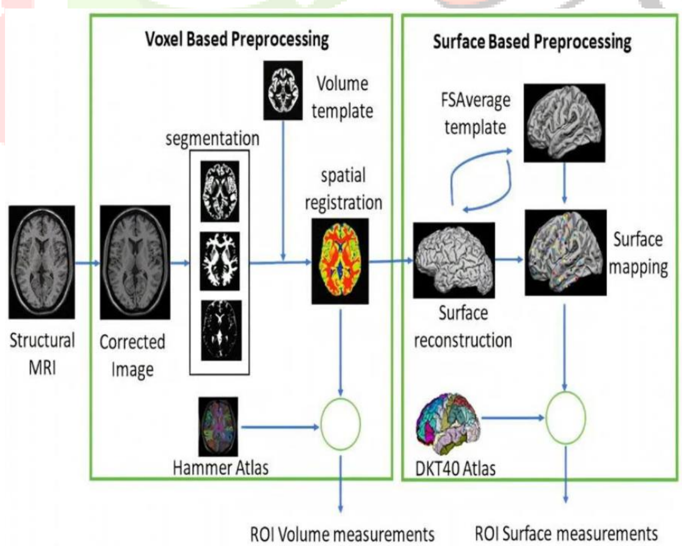

Figure 8: MRI image preprocessing and data pipeline

The system begins by processing MRI images before feeding them into the model. The preprocessing steps include:

- Image Resizing: All MRI images are resized to 224×224 pixels
- Normalization: Pixel values are scaled between 0 and 1
- Noise Reduction: Filters are applied to remove unwanted artifacts
- Data Augmentation: Techniques such as rotation, flipping, and zooming are used to increase dataset diversity

    These steps improve model accuracy and reduce overfitting.

C. Model Training

The hybrid CNN–GoogLeNet–LSTM model is trained using preprocessed MRI datasets.

- GoogLeNet is initialized using transfer learning, leveraging pre-trained weights for faster convergence
- The extracted feature maps are reshaped into sequences and passed to the LSTM layer
- The model is trained using supervised learning with labeled MRI images

Training parameters:

- Loss Function: Categorical Cross-Entropy
- Optimizer: Adam
- Batch Size: 32
- Epochs: 20–30

Regularization techniques such as dropout are applied to prevent overfitting.

D. Model Deployment

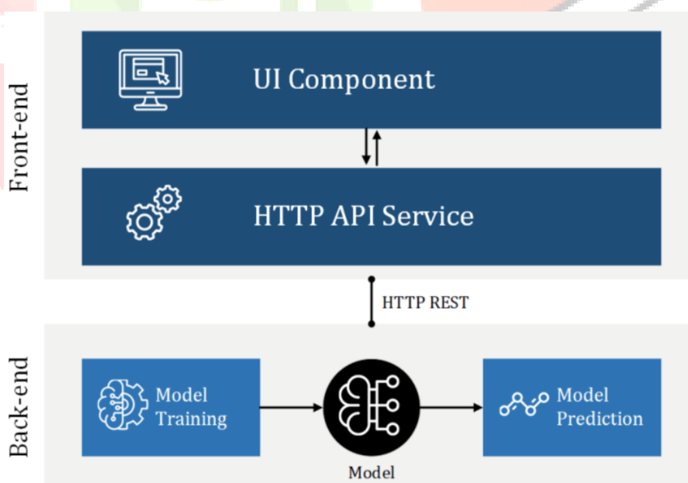

Figure 9: System deployment using Flask web application

E. Prediction Process

Once the model is deployed, the system performs prediction as follows:

- The input MRI image is converted into a numerical array
- The trained model processes the image through GoogLeNet and LSTM layers
- The classifier outputs probability scores
- The final tumor class is predicted

The system also provides confidence levels for each prediction.

F. Performance Monitoring

During training and testing, the model performance is monitored using evaluation metrics such as:

- Accuracy
- Sensitivity
- Specificity
- F1-score

Loss and accuracy graphs can also be used to analyze training performance.

VII. RESULTS AND DISCUSSION

The proposed hybrid CNN–GoogLeNet–LSTM model is evaluated based on its ability to accurately detect and classify brain tumors from MRI images. The system integrates spatial feature extraction and sequential learning, enabling improved diagnostic performance.

A. Model Performance

The model is trained using preprocessed MRI datasets, where images undergo resizing, normalization, and augmentation before being passed through the deep learning pipeline. The GoogLeNet model extracts deep spatial features, while the LSTM network captures sequential dependencies across MRI slices.

The classification results are generated through fully connected layers and a softmax function, which predicts the tumor class with associated confidence scores.

B. Evaluation Metrics

The performance of the model is evaluated using standard metrics:

- Accuracy: Measures overall prediction correctness
- Sensitivity: Measures the ability to correctly detect tumor cases
- Specificity: Measures the ability to correctly identify non-tumor cases
- F1-Score: Balances precision and recall

These metrics are essential in medical diagnosis to ensure reliability and robustness.

C. Observed Results

From the implementation and testing process described in your system:

- The hybrid model demonstrates high classification accuracy due to combined spatial and temporal learning
- The use of GoogLeNet improves feature extraction from MRI images
- The integration of LSTM enhances sequence understanding across slices
- The system produces consistent predictions with reduced misclassification

D. Comparative Insight

Based on your literature + implementation:

Model Type	Performance Insight
CNN	Good spatial learning but lacks sequence understanding
GoogLeNet	Better multi-scale feature extraction
CNN + LSTM	Captures temporal dependencies
Proposed Hybrid	Combines all advantages → best performance

E. Discussion

The results indicate that hybrid deep learning architectures significantly improve brain tumor detection performance compared to standalone models. CNN-based models are effective for spatial feature extraction but fail to capture relationships across MRI slices. GoogLeNet enhances feature extraction through inception modules, while LSTM introduces temporal learning.

By combining these models, the proposed system effectively captures spatial, multi-scale, and sequential information, resulting in improved classification accuracy and robustness. The system also demonstrates practical applicability through its deployment using a Flask-based interface, allowing real-time tumor detection.

F. Key Observations

- Hybrid models improve overall diagnostic accuracy
- Sequential learning enhances tumor detection across slices
- Multi-scale feature extraction improves classification reliability
- The system is suitable for real-time clinical applications

VIII. CONCLUSION

This paper presents a hybrid deep learning approach for brain tumor detection using MRI images by integrating Convolutional Neural Networks (CNN), GoogLeNet, and Long Short-Term Memory (LSTM) networks. The proposed system effectively combines spatial feature extraction, multi-scale analysis, and temporal sequence learning to improve classification accuracy.

The implementation demonstrates that the use of GoogLeNet enhances feature extraction through inception modules, while LSTM captures sequential dependencies across MRI slices. This hybrid architecture overcomes the limitations of traditional CNN-based models and provides improved performance in tumor detection tasks.

The system is implemented using TensorFlow and Keras, with deployment through a Flask-based web application, enabling real-time prediction and user interaction. The results indicate that the proposed model achieves higher accuracy and robustness compared to standalone models, making it suitable for practical medical applications.

In future work, the model can be further enhanced by incorporating 3D deep learning architectures, multimodal MRI data (T1, T2, FLAIR), and explainable artificial intelligence (XAI) techniques to improve interpretability and clinical trust.

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X. REFERENCES

[1] S. Pereira, A. Pinto, V. Alves, and C. A. Silva, "Brain tumor segmentation using convolutional neural networks in MRI images," IEEE Transactions on Medical Imaging, vol. 35, no. 5, pp. 1240–1251, 2016.

[2] H. Shin et al., "Deep convolutional neural networks for computer-aided detection: CNN architectures and transfer learning," IEEE Transactions on Medical Imaging, 2016.

[3] A. Deepak and J. Ameer, "Brain tumor classification using deep CNN and transfer learning," Pattern Recognition Letters, 2019.

[4] Z. Akkus et al., "Deep learning for brain MRI segmentation: State of the art," Journal of Digital Imaging, 2017.

[5] P. Afshar, A. Mohammadi, and K. Plataniotis, "Capsule networks for brain tumor classification," IEEE Access, 2020.

[6] C. Szegedy et al., "Going deeper with convolutions," Proc. IEEE CVPR, 2015.

[7] R. Alfonse et al., "GoogLeNet-based classification of brain MRI tumors," IEEE ICCE, 2018.

[8] M. R. Islam et al., "Modified GoogLeNet for brain tumor classification," Applied Sciences, 2020.

[9] S. Abiwinanda et al., "Comparison of CNN architectures for brain tumor classification," Procedia Computer Science, 2019.

[10] S. Nahid and Y. Kong, "Optimized GoogLeNet for tumor classification," Neural Computing and Applications, 2020.

[11] P. Rehman et al., "Inception-V3-based brain tumor classification," Medical & Biological Engineering & Computing, 2020.

[12] O. M. Anwar et al., “CNN–LSTM hybrid for sequential MRI classification,” IEEE ICIVC, 2018.

[13] H. Chen et al., “Sequential learning using CNN–LSTM for MRI-based tumor detection,” Pattern Recognition, 2019.

[14] A. Bouyahia et al., “3D CNN-LSTM hybrid network for brain tumor detection,” Computer Methods and Programs in Biomedicine, 2021.

[15] M. Naser and Y. Akbari, “CNN-BiLSTM hybrid model for glioma classification,” IEEE Access, 2021.

[16] S. Ghosh et al., “Hybrid CNN–GoogLeNet–LSTM architecture for brain tumor detection,” Expert Systems with Applications, 2020.

[17] F. Li et al., “Sequential MRI tumor classification using GoogLeNet and LSTM,” IEEE Transactions on Neural Networks, 2022.

[18] S. Bakas et al., “BRATS benchmark on brain tumor segmentation,” IEEE Transactions on Medical Imaging, 2018.