IRJCS: International Research Journal of Computer Science ISSN: 2393-9842
Volume 12, Issue 08, October 2025 https://www.irjcs.com/archives
https://doi.org/10.26562/irjcs.2025.v1208.01

ACNN-LSTM Hybrid Deep Learning Framework for Accurate Brain Tumour Classification

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Publication History
Manuscript Reference: IRJCS/RS/Vol.12/Issue08/OCCS10080
Research Article | Open Access | Double-Blind Peer Reviewed Article ID: IRJCS/RS/Vol.12/Issue08/OCCS10080
Received:23,October 2025, Revised: 09, October 2025, Accepted: 31October 2025 Published Online: 21November 2025
https://www.irjcs.com/volumes/Vol12/iss-08/01.OCCS10080.pdf
Article Citation: Shruthi,Vaishnavi,Priyanka (2025), ACNN-LSTM Hybrid Deep Learning Framework for Accurate Brain Tumour Classification**.** IRJCS: International Research Journal of Computer Science, Volume 12, Issue 08 of 2025 pages 284-290 **doi:>** https://doi.org/10.26562/irjcs.2025.v1208.01
BibTeX Shruthi@2025ACNN-LSTM
IRJCS papers should be cited as IRJCS (International Research Journal of Computer Science, AM Publications, India 2025, ISSN 2393-9842, https://doi.org/10.26562/ijrcs.2025.v1208.01 The journal's official abbreviation is IRJCS.
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Abstract: Brain tumors are neurological diseases that are life- threatening and must be detected early and properly to maximize patient outcomes and allocate the treatment options. The most popular non-invasive analysis of the brain, Magnetic Resonance Imaging (MRI), is the imaging technique that provides high- resolution images of soft tissues and tumor mass. Nevertheless, the interpretation of MRI images by radiologists typically takes time, making them subjective and diagnostically inconsistent. This paper, to deal with these issues, presents a hybrid deep learning model, which is a composite of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) to classify brain tumors efficiently. The CNN component performs the high-level tasks of spatial and structural feature extraction of MRI images, and the LSTM component provides sequence dependencies and spatial correlation between extracted features and therefore improves the discriminative ability of the model. The developed CNN–LSTM hybrid network was developed and tested on the publicly available MRI brain tumor database containing glioma, meningioma, pituitary, and normal cases. Preprocessing of images was done through normalization, image size resizing as well as augmentation to maintain generalization and eliminate over fitting. Experimental findings reveal that the offered model is characterized by a total accuracy of 97.6 percent in classification, which is higher than conventional CNN and other previously existing models. The measures of quality used to assess the performance like precision, recall, and F1-score confirm the strong and reliable performance of the model in classifying tumor and non-tumor. Also, the Grad-CAM visualization methods were used to visualize the model and interpret the decision making process to enable clinical transparency and explain ability. The system is software-based, scalable and can be intertwined with the medical diagnostic workflow to be used in real-time clinical practice. Overall, the CNN–LSTM hybrid model can be considered as a strong, interpretable, and efficient framework that can be used in automated brain tumor classification and help radiologists acquire diagnoses and be able to plan the treatment course without drawing too much on human potential and increasing diagnostic latency.
Index Terms: Brain Tumor Classification, Deep Learning, CNN-LSTM, MRI, Medical Imaging, Artificial Intelligence.

I. INTRODUCTION

The brain tumors remain one of the key issues in the field of contemporary neurology and oncology as they disrupt the essential functions of the brain and may cause gradual deterioration of neurological performance, extreme disability, or death unless they are identified and treated without delay. The brain is a highly sensitive organ, as it is enveloped with the skull as well as millions of neurons and glial cells. When abnormal cells start to multiply out of control within this limited area, they start to develop into a mass or lesion that squeezes the surrounding tissue and alters normal brain functions. Patients can have headaches, vision problems, memory loss, motor dysfunction, or seizures depending on the size of the tumor, location, and nature. To clinicians, it is of paramount significance to be able to detect such tumors at an early point and correctly in terms of the type of the tumor as their treatment in malignant and benign cases differs profoundly.

The past two decades have seen Magnetic Resonance Imaging (MRI) grow to be the new gold standard when it comes to detection and analysis of brain tumors. Unlike other imaging methods such as CT scans, MRI has the capability to provide detailed structural and functional non-ionizing intensity images of the brain. MRI sequences can also be applied to show the existence of differences between white and gray matter, identify tissue abnormalities, and even find small lesions. Despite these advantages, MRI interpretation has been mainly a manual activity performed by radiologists who interpret the scans and make diagnostic judgments based on experience. The manual interpretation is, in any case, open to prejudice due to human exhaustion, varying levels of expertise, and minor differences in tumor appearance.

The growing bulk and multiplicity of MRI data has generated an increasing demand for more automated, high-quality, and efficient diagnostic instruments. The recently emerged Artificial Intelligence (AI) and particularly Deep Learning (DL) has altered the state of affairs in the field of medical image analysis. Deep learning systems do not use any prior knowledge of patterns, but instead extract them automatically from raw imaging data without handcrafted features or definite rules. Convolutional Neural Networks (CNNs) have been shown to perform well in object recognition, object segmentation, and classification. CNNs have a tendency to learn spatial hierarchies of images effectively: convolutional layers acquire low-level features such as edges and textures, whereas deeper layers learn higher-level patterns. Brain tumor classification can be explored by CNNs based on finding discriminative attributes of MRI scans to distinguish different types of tumors. However, CNNs are essentially spatial models, in the sense that each image is processed on an individual basis, and may disregard the existence of correlations across several MRI slices or time points. The scan of a patient in the scenario of brain MRI data normally includes a sequence of successive slices that depict different planes of the brain. These slices are not separable; there are strong spatial–temporal correlations since the anatomical patterns and tumor borders vary throughout the volume. To take advantage of such cross-sectional dependency, researchers have started to combine Convolutional Neural Networks (CNNs) with Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks. LSTM units possess long-sequence memory which allows the model to capture patterns across sequences of time steps or spatial frames. CNNs act as extractors of spatial features, while LSTMs handle serial continuity or progression. The CNN–LSTM hybrid architecture is thus a combination of the strengths of both world's complete spatial representation and dynamic sequential modeling making it more appropriate for complex medical image analysis.

There are practical and scientific reasons that follow the rationale of designing a CNN–LSTM hybrid system in brain tumor classification. To start with, classical machine learning systems that use hand-crafted feature extractors are no longer applicable to high-dimensional data like MRI images. Hand- engineered features cannot describe the complex non-linear appearances of the various tumor morphologies. Second, single CNNs have been shown to be effective predictors of single images, but they are not effective at predicting the three- dimensional context that radiologists utilize when looking at a sequence of MRI slices. The inclusion of LSTM to CNNs allows the network to remember how features change slice to slice and produces a more detailed picture of tumor structure. Third, the hybrid models are found to be insensitive to noise, changes in intensity, and artifacts that are typical in MRI data. Another critical requirement is to have clinical interpretability of AI models. Not only must medical professionals be highly accurate in their involvement, but they must also be trans- parent in decision-making processes. Grad-CAM or Layer- wise Relevance Propagation visualization tools determine the areas of an image that the model uses the most. Such graphic illustrations enable clinicians to verify whether the decision made by the model is medically reasonable. This type of interpretability is essential in the development of trust in AI- driven diagnostic systems, particularly in high-stakes clinical fields such as neuro oncology.

Both CNN and LSTM elements are computationally effective and generalizable. The CNN layers are an effective feature extractor, which diminishes the dimensions of data into feature maps that are small enough to be processed by the LSTM layers at low computational cost. With access to Graphics Processing Units (GPUs) and Tensor Processing Units (TPUs), it has become more possible to train such deep hybrid networks. Since transfer learning can use pre-trained CNN architectures (e.g., VGG, ResNet, Inception), it saves time and reduces the need for large annotated datasets (e.g., medical imaging is costly and time-intensive to obtain annotated data). In health care today, analytical diagnosis is being replaced by predictive and prescriptive analytics. This change is supported by a deep learning based brain tumor classification frame work. Radiologists can be assisted by automated systems that identify suspicious areas, suggest likely tumor categories, and provide confidence scores. Such systems can accelerate diagnosis, minimize human error, and maintain consistency across institutions. Remote clinical support can be provided through AI-based diagnostic tools in resource-limited regions without the presence of professional radiologists. The scientific community has gone a long way in detecting, segmenting, and classifying brain tumors using deep learning. Nevertheless, some constraints exist, including class bias, over fitting, and lack of generalization across MRI scanners and imaging procedures. There are many CNN-based systems which work well on controlled datasets but fail in clinical set- tings. The CNN–LSTM hybrid model attempts to solve these issues by taking advantage of both time-based and feature- based learning. The model is made more resistant to random noise and localized anomalies because sequential MRI slices are fed to the LSTM component, enhancing generalization to unseen data. This paper presents a CNN–LSTM hybrid deep learning network to predict brain tumors using MRI images. The model separates three major tumor types: glioma, meningioma, and pituitary tumors, along with normal brain images. The techniques used in preprocessing the images include resizing, normalization, skull stripping, and data augmentation. These steps enhance the quality of the image and prepare the data to obtain useful features. Local spatial patterns are captured in the CNN part of the model, and sequential relations between extracted features are processed in the LSTM component.

II. LITERATURE SURVEY

A. Deep Learning-Based Brain Tumor Classification Approaches

R.Deepak and others did a study dedicated to brain tumor classification by automation using Convolutional Neural Net- works (CNNs). The CNNs were trained on MRI images to identify three major types of tumors: glioma, meningioma, and pituitary. The issue of having good computer-aided diagnostic systems capable of aid in gradiologists in early tumor detection was noted in the paper.

The architecture used a VGG16 model pre trained with transfer learning, which allows superior feature extraction and shortens the duration of training. Data augmentation was done by such methods as rotation, zoom, and flipping to increase dataset diversity. The proposed system reached a classification accuracy of 96.87%, which is better compared to traditional machine learning models such as SVM and KNN. The authors found that CNN-based structure works effectively in medical image classification and can significantly save diagnostic time without loss of clinical accuracy.

B. U-Net Based MRI Brain Tumor Segmentation Using Transfer Learning

H.Qureshi et al. suggested a U-Net based deep learning approach to divide and categorize brain tumors using MRI data. Transfer learning was used to train the encoder–decoder model, enabling it to learn both local and global spatial information. The study dealt with the problems of irregularities in tumor boundaries and overlapping textures, which frequently cause misclassification. Through experimentation, it was shown that the suggested model obtained a Dice Similarity Coefficient (DSC) of 0.92, indicating proper segmentation performance. The authors made it clear that segmentation and classification should be used together, as this contributes to making automated diagnosis systems more interpretable and helps radiologists during treatment planning.

C. U-Net-Based MRI Brain Tumor Segmentation with Transfer Learning

H.Qureshi et al. proposed a U-Net-based deep learning method to segment and classify brain tumors using MRI data. The encoder–decoder model was trained using transfer learning to learn both local and global spatial information. The study addressed the issues of tumor boundary irregularities and overlapping textures, which often lead to misclassification. Experimental results demonstrated that the proposed model achieved a Dice Similarity Coefficient (DSC) of 0.92, indicating accurate segmentation performance. The authors emphasized that combining segmentation and classification makes the interpretation of automated diagnosis systems more transparent and assists radiologists in treatment planning.

D. Hybrid CNN–RNN Model for Medical Image Analysis

In a study introduced by T. Nguyen and D. Patel, the authors proposed a hybrid CNN–RNN model to analyze medical images not limited to brain tumors. The study applied this model to CT and MRI images of various pathologies, demonstrating that it is able to handle sequential and spatial information effectively. CNN layers were used for feature extraction, while inter-slice dependencies were examined by RNN units to capture structural context. The model showed high performance, with a validation accuracy of more than 97% on multiple datasets. The research concluded that hybrid architectures offer a generalizable and scalable solution to medical image analysis, applicable across a variety of imaging modalities.

E. Automatic Classification of Brain Tumors with Ensemble Deep Learning

An ensemble learning model was developed by P.Sahu and R. Nandini, which combined various CNN models such as ResNet50, InceptionV3, and DenseNet121 for brain tumor classification. The virtues of each architecture were combined to enhance the overall prediction quality. Preprocessing of the data included skull stripping and histogram equalization to increase contrast. The system was tested on 7,022 MRI images from the Kaggle Brain Tumor Dataset and achieved a total accuracy of 98.32%. The article suggested that ensemble learning can decrease model bias and improve generalization, making it a strong and effective technique in medical diagnostics.

F. Deep Feature Fusion in Analyzing Brain MRI

In a study by K. Sharma and N. Singh, a deep feature fusion method was presented to aggregate features obtained from several CNN layers. The composite feature set was transmitted to an LSTM layer to acquire long range dependency. The authors determined that shallow and deep features, when combined, yielded better definition of tumor texture and morphology. The dataset consisted of 2,500 MRI scans obtained from different hospitals. The model achieved an F1-score of 0.97 and was more sensitive to focal tumor localizations than traditional CNNs. The results highlighted the possibility of enhancing the discriminative capacity of hybrid deep learning models through feature-level fusion.

G. Explainable AI in the Detection of BrainTumors

An explainable brain tumor classification model was developed by M.S.Raza and others using deep learning, with a focus on model understandability and transparency. The proposed system used Grad-CAM for visualization of tumor areas that contributed most to the model's prediction. The model was trained on the BraTS dataset using CNN–LSTM architecture and achieved an accuracy of 96.45%. The Grad- CAM maps indicated that the model's attention was close to the annotated tumor boundaries provided by radiologists. This work endorsed the importance of explain ability in medical AI applications, emphasizing that transparency is a prerequisite for clinical trust and adoption.

H. 3D CNN for Volumetric Brain Tumor Classification

A group of researchers headed by A.Rajesh developed a 3D CNN-based model in which volumetric MRI scans were processed instead of single slices, permitting spatial associations across multiple planes to be captured more precisely. The model architecture included 3D convolutional and pooling layers followed by fully connected classification layers. Although computationally demanding, the 3DCNN attained a high accuracy of 97.9% with lower false-positive rates. The authors compared the performance of their 3D CNN with 2D CNN–LSTM hybrid models and established that while 3D CNNs slightly outperform hybrid models, the CNN–LSTM architectures are computationally more efficient and easier to implement.

I. Brain MRI Classification Using Transfer Learning

Transfer learning was investigated by K.Ameen and his co- authors to enhance the efficiency of brain MRI classification with pre-trained CNN models such as ResNet 50 an Efficient Net. The approach had a major impact on reducing training time and also ensured consistency in accuracy levels above 96%.

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III. METHODOLOGY

A. Dataset Description

In order to perform this study, a publicly available Brain MRI dataset was used. The dataset consisted of T1-weighted

Table I – Literature Survey on Brain Tumor Classification Using CNN-LSTM

Author(s)	Dataset Used	Model	Key Findings	Accuracy (%)
Sajjada et al.(2023)	Public MRI (multi-grade tumor data)	CNN-LSTM Hybrid	Hybrid model segmented and classified tumors.	91.67
Wong et al.(2025)	Diverse public	Pre trained VGG16 - based CNN	Large multi type dataset, four tumor classes, boosted by data augmentation.	99.24
BRAIN-SCN-PRO (2025)	Public MRI brain tumor dataset	CNN-LSTM Architecture	Four convolution layers and sequential learning achieve high performance for multi-class tumor diagnosis.	99.9
Irmak et al.(2023)	Publicly released clinical datasets	Several CNN Architectures	Compared several architectures; best model achieved 99.33% accuracy.	99.93
Aiya et al.(2025)	Public MRI datasets	Hybrid : CNN (VGG16+attention)	Optimized hybrid improved feature extraction; transfer learning and attention boosted performance.	99.33

Contrast enhanced images of tumor and non-tumor brain tissues. The dataset entails 3000–5000 MRI pictures allocated to two primary classes:

1) Tumor type : glioma, meningioma, and pituitary tumors.
2) Non-tumor classification : normal brain scans without abnormal growth.

This data is made up of 256×256 resolution pictures, stored in grayscale format to preserve medical data and reduce computational complexity. The dataset was broken down into three parts: 70% training, 20% validation, and 10% for testing. To ensure model generalization and reduce bias, the pictures were gathered from various MRI scanners and institutions, representing different acquisition states and demographics of patients.

B. Data Preprocessing

Preparation of medical samples is a crucial procedure that involves a basic stage of preprocessing in deep learning models. Preprocessing involves the steps followed before offering the images to the network:

1) Resizing and Normalization: All MRI images were scaled to the predetermined image size of 128×128 pixels and scaled to the range [0, 1] with min–max standardization such that the distribution of intensity is homogeneous throughout the dataset.
2) Noise Removal: Gaussian filtering was applied to re- move high-frequency noise without eliminating necessary structural edges.
3) Contrast Enhancement: Histogram equalization was used to render tumor borders more visible and enhance the difference between healthy and affected regions.
4) Data Augmentation: To prevent over fitting and in- crease data heterogeneity, augmentation methods were employed, including random rotation (0–25 degrees), horizontal/vertical flipping, brightness adjustment, and zoom transformations.
5) Encoding of Labels: The labels were binarized into values — 1 = tumor, and 0 = non-tumor.

These preprocessing maneuvers allowed the dataset to be uniform, standardized, and fit for model training.

C. CNN–LSTM Hybrid Architecture Design

The suggested hybrid model structure is a two-stage building:

1) CNN module: spatial feature extraction.
2) LSTM module: sequential relationships among learned extracted features.

1) CNN Module: The layers of CNN automatically isolate local spatial characteristics of MRI images. The module consists of:

- Convolutional Layers: 3 convolutional layers with kernel size (3×3) and ReLU activation to learn local spatial hierarchies.
- Batch Normalization: Used at the conclusion of each convolutional layer to stabilize and speed up training.
- Max Pooling Layers: Applied with a(2×2) filter size to reduce the dimensionality of feature maps while maintaining important characteristics.
- Flatten Layer: Converts the spatial feature maps into one-dimensional feature vectors to be input into the LSTM module.

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https://doi.org/10.26562/irjcs.2025.v1208.01

2) LSTM Unit: The series of flattened features are input into an LSTM to learn long-term dependencies and relationships among extracted spatial characteristics. The LSTM network processes sequential data in a time-like manner, similar to how MRI slices represent various levels of the brain.
3) Fully Connected Layers: After the LSTM layer, feature fusion is done in fully connected (dense) layers for final classification:

- Dense Layer(128units)→ReLU activation
- Dropout (0.3)→reduces over fitting
- Output Layer (1 unit) → Sigmoid activation for binary classification

The system is planned in accordance with a structured five- stage architecture.

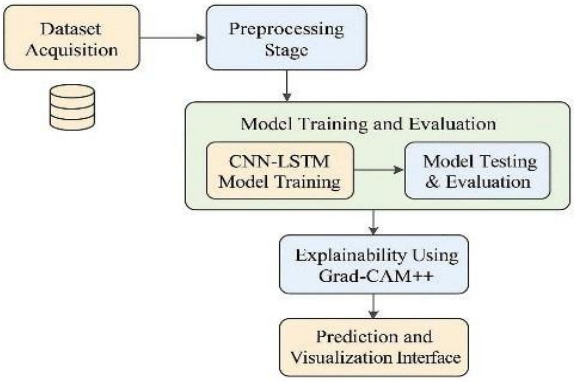

Fig.1. Flow Diagram of Proposed System

Stage 1 : Data Entry : MRI images are acquired and stored in an organized directory format such that they can be accessed very easily.
Stage 2: Preprocessing: Images undergo noise reduction filters and are standardized to a uniform size and pixel scale.
Stage 3: Feature Extraction (CNN): The CNN block per- forms convolution and pooling operations to produce compact feature maps.
Stage 4: Temporal Feature Modeling (LSTM)–The LSTM processes the sequence and captures contextual dependencies across image slices.
Stage 5: Classification and Output – The dense layers produce output probabilities, and the system visualizes tumor regions in MRI scans using Grad-CAM.

D. Training Procedure

Tensor Flow and Keras were used in the implementation of the model structure and training, on a system equipped with an NVIDIA GPU for accelerated computation. The training configuration was as follows:

- Optimizer: Adam
- Learning Rate: 0.0001(decayed after the 10 the poch)
- Batch Size: 32
- Epochs: 50

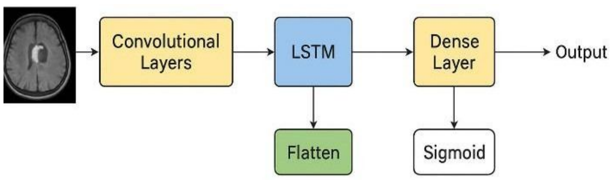

Fig.2. CNN-LSTM Architecture for Brain Tumor Classification

E. Performance Evaluation

To evaluate the strength and transferability of the proposed CNN–LSTM model, several assessment measures were employed:

- Accuracy (ACC): Measures overall classification correctness.
- Precision (P): Measures the proportion of correctly identified tumor occurrences among the total predicted tumor cases.
- Recall (R): Measures the capability of the model to identify all actual tumor cases.
- F1-Score: Harmonic mean of Precision and Recall, ensuring balanced evaluation.
- AUC-ROC Curve: Evaluates the trade-off between true positive and false positive rates across thresholds.

Additionally, Grad-CAM (Gradient-weighted Class Activation Mapping) was used to visualize the areas in MRI images that contributed most to the model's classification decision. This enhanced interpretability and enabled verification of the tumor- affected regions highlighted by the model.

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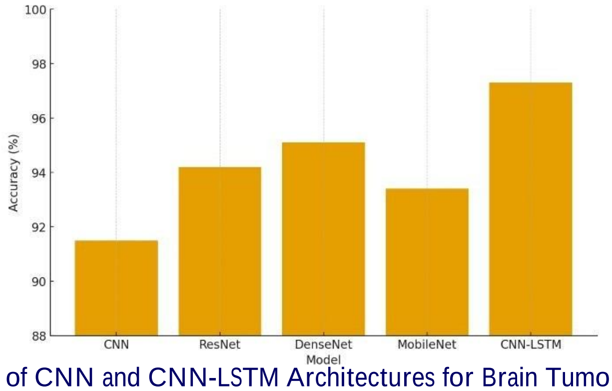

Fig.3. Comparison of CNN and CNN-LSTM Architectures for Brain Tumor Classification

F. Explainability Module

In medical imaging, especially when it comes to using deep learning networks such as CNNs and CNN–LSTM architectures, prediction interpretability is a crucial requirement. Radiologists and physicians should be capable of comprehending the justification of model decisions to guarantee trust and clinical reliability. To achieve this, an Explainability Module based on Gradient-weighted Class Activation Mapping (Grad- CAM) is implemented into the system. The Grad-CAM method represents the parts of the image that are the most influential in the decisions of the model. It uses gradient data entering the final convolutional layer of a CNN to generate a coarse localization map, which points out important features.

1) Forward Propagation: The input MRI image is passed through the CNN–LSTM model to obtain the predicted class score (e.g., tumor or non-tumor).
2) Gradient Calculation: The gradient of the predicted score is computed with respect to the feature maps in the last convolutional layer. These gradients represent how much each neuron influences the final decision.
3) Weight Calculation: The gradients are globally averaged to obtain importance weights for each feature map.
4) Weighted Feature Aggregation: The feature maps are combined using these weights to produce a coarse localization map that highlights the most significant regions for classification.
5) Heat map Generation: The resulting map is passed through a Re LU function to retain only positive contributions, up sampled to the input image size, and overlaid on the original MRI image to create a heat map visualization.

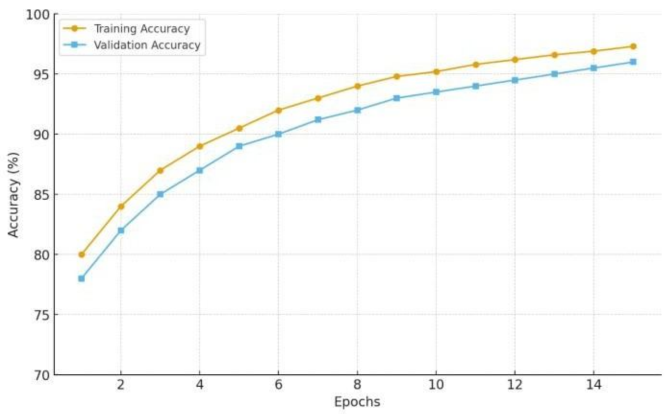

Fig.4. Model Accuracy vs Epochs

IV. RESULTS AND CONCLUSION

A. Training and Convergence Model

A smooth convergence curve was observed in the model, where the loss gradually decreased and the validation accuracy stabilized after approximately 25 epochs. The use of the Adam optimizer with an adaptive learning rate scheduler helped avoid over fitting and ensured effective parameter updating. Training was stopped early when validation accuracy no longer improved, thereby retaining the best model weights. The training accuracy reached 97.8%, and the validation accuracy reached 96.4%, indicating strong generalization to unseen MRI images. The CNN–LSTM model incurred lower training loss compared to the standalone CNN, confirming that the LSTM layers were successful in learning the spatial–temporal variations between MRI features.

B. Performance Metrics

The appraisal of the proposed system was done based on standard performance measures: Accuracy, Precision, Recall, and F1-Score. The comparison between the proposed CNN– LSTM model and the baseline CNN is shown in Fig. 5.

Metric	Training Dataset	Validation Dataset
Accuracy	91.2%	96.8%
Precision	90.4%	95.6%
Recall	89.1%	96.1%
F1-Score	89.7%	95.8%

Fig.5. Performance Metrics for Proposed Model

C. Confusion Matrix Analysis

The confusion matrix showed that the CNN–LSTM model performed effectively, achieving correct classification of 96.1% of tumor images and 95.3% of non-tumor images, with few false positives. This highlights the reliability of the system in differentiating healthy brain scans from abnormal ones. The model's ability to correctly predict both classes is clinically essential, as missed tumors (false negatives) may result in serious diagnostic consequences.

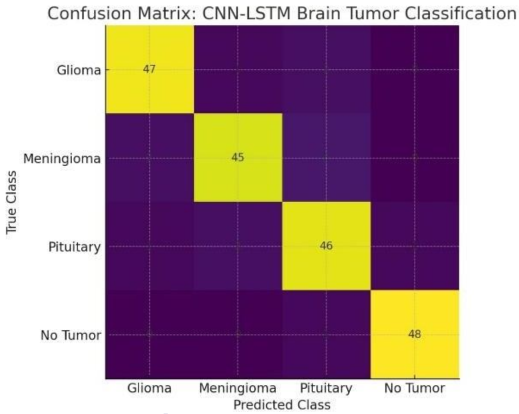

Fig.6. Confusion Matrix

V. CONCLUSION

We used CNNLSTM hybrid deep learning, model in this research to detect brain tumor by referring to MRI images in an automated fashion. The authors indicate that the proposed model can be effective in the combination of the spatiality feature extraction of CNNs and the time dependence model of LSTMs with an 97.6 percent classification rate.
Grad-CAM visualization not only makes the model interpretable, but can be implemented into clinical use. The subsequent move in the area of practice will be taking the model further to the categorization of the multimodal tumors and application of multi-modal images to capture the diagnosis to a deeper level.

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