

Integration Of VGG Network For Accurate Brain Tumor Detection Using MRI Scan

Leena Sulbhewar^{1*}, Prof. Rahul Bhandekar², Prof. Shrunkhala Raut³, Dr. Jagdish Pimple⁴, Dr. Praveen Sen⁵, Dr. Vishal Tiwari⁶, Dr. Sweta Raut⁷

¹Department of Computer Sci. & Engineering Wainganga College of Engineering and Management, Nagpur, India. Sulbhewar.leena@gmail.com

²Department of Computer Sci. & Engineering Wainganga College of Engineering and Management, Nagpur, India. bhandekar.r@wcem.edu.in

³Department of Computer Sci. & Engineering Wainganga College of Engineering and Management, Nagpur, India.

⁴Department of Information Technology, St. Vincent Pallotti College of Engineering & Technology Nagpur, India. pimplejagdish@gmail.com

⁵Department of Computer Sci. & Business System, St. Vincent Pallotti College of Engineering & Technology Nagpur, India. psen@stvincentngp.edu.in

⁶Department of Information Technology, St. Vincent Pallotti College of Engineering & Technology Nagpur, India. vtiwari@stvincentngp.edu.in

⁷Department of Computer Sci. & Engineering, Jhulelal Institute of Technology, Nagpur, India, sweta.a.raut@gmail.com

Abstract: Brain tumour is one of the most aggressive malignant cancers and early-accurate diagnosis may increase the changes in successful treatment and subsequently improvement in patient's survival. Magnetic Resonance Imaging (MRI) is currently the gold standard diagnostic technique, but manual interpretation becomes slow, unreliable and radiologist skill-dependent when applied to large numbers of images. To overcome these limitations, in this work, we propose an automated deep learning-based brain tumor detection framework using transfer learning with VGG16 and VGG19 models. Both the models were pre-trained and fine-tuned using a brain MRI dataset, and their performance was measured in terms of accuracy, loss, precision, recall and F1-score. The experimental results show a trade-off between performance and efficiency: VGG19 achieves better accuracy at the cost of slower convergence time and heavier computation, whereas VGG16 provides faster convergence rate with less cost. In the interest of transparency and clinical confidence in these predictions, we used explainable AI (XAI) methods – namely Grad-CAM, LIME, and SHAP – to generate visual level as well as feature-level explanations of how each model makes its predictions. The deployed models along with the XAI outputs were implemented with a web-based framework written in Flask, which allows real-time MRI upload, prediction and visualization of interpretability map. We showed the advantage of integrating deep learning, explainability, as well as deployment for robust and interpretable brain tumor diagnostic assistance.

Keywords: Brain Tumor Detection, MRI, Deep Learning, VGG16, VGG19, Medical Imaging, Explainable AI, Grad-CAM, LIME, SHAP

1. INTRODUCTION

Brain cancers are one of the most lethal neurological diseases, and timely and accurate diagnosis is necessary to increase patient survival. Magnetic Resonance Imaging (MRI) is the most adopted imaging method for brain tumor diagnosis but manual MRI scan analysis has some drawbacks. It is time-consuming, subjective in nature and highly affected by the skill of radiologists. These challenges emphasize the requirement of automated and robust diagnostics tools for clinical decision making. Recent advances in artificial intelligence (particularly deep learning (DL) methods using Convolutional Neural Networks (CNNs)) have shown great success in medical image analysis making the fast, reliable, and accurate predictions possible. In this state of the art we suggest a transfer learning method that uses VGG16, and VGG19 with respect to two classes -

tumor (and) or non-tumor. Comparisons and evaluations of two models are provided to demonstrate their efficiency in brain tumor diagnosis. Although deep learning models have strong discriminatory power, they are frequently criticized based on the “black-box” problem that makes them less acceptable for clinical use. To mitigate this, the proposed framework incorporates explainable artificial intelligence (XAI) methods such as Gradient-CAM, LIME, and SHAP. These are visualization methods that uncover and visualize important regions and features contributing to model predictions, increasing transparency of the model, and trust on the part of clinicians. In addition, the trained models and XAI methods are implemented in a web application based on Flask framework, where users upload MRI scans to get instant classification results and interpretability visualization. The presented approach shows how deep learning combined with explainable AI and user-friendly deployment can contribute to that effort of equipping radiologists for trustworthy, reliable diagnosis in brain tumors.

II. LITERATURE REVIEW

Recent works have shown that deep learning has promising potentials on brain tumor detection in MRI images, especially CNNs. Deep neural networks like VGG16, for example, have demonstrated good feature extraction and classification capacities when transferred skills are used. These models are capable of reaching good performance on medical imaging data also when only a small amount of such data is available owing to the use pre-trained weights on ImageNet. Nevertheless, the interpretability of traditional CNN models is limited due to their poor explainable ability, thus constraining their application in clinic.

To mitigate this deficiency, explainable artificial intelligence (XAI) approaches including Gradient-weighted Class Activation Mapping (Grad-CAM), Local Interpretable Modelagnostic Explanations (LIME), and SHapley Additive exPlanations (SHAP) have attracted more interest. Using these approaches, we gain visual and quantitative understanding of model predictions, facilitating clinical intuitions of decision making while also building up confidence in our automated systems. Researches have shown the importance of incorporating interpretability approaches into CNN based frameworks to improve diagnosis performance and clinical acceptance. Some studies investigated CNN-based methods for brain tumor detection. In [1], the use of deep learning CNN architecture is proposed for tumor detection and segmentation on MRI images, where it captures spatial properties of a tumor by multiple convolution and pooling layers. This research not only demonstrates the significance of early detection but also attains a high level of accuracy, precision, and recall, validating that CNN architecture is far better in medical image processing. Likewise, [4] provides a CNN architecture which is optimized for fast MRI processing and exhibits better classification performance as well as higher efficiency in comparison to conventional approaches such that it can be directly used for healthcare practice.

Explainable AI have been added to brain tumor detection systems for increasing transparency. The work [2] combines XAI methods, such as Grad-CAM and LIME with CNN-based classification to create a visualization of the decision regions and makes this task interpretability to clinicians. The findings suggest that trust in an automated diagnostic system is improved when one increases the affordance of understanding/believing why a system has made a certain recommendation beyond simply being accurate. In addition, [3] addresses the state-of-the-art deep learning architectures as well as preprocessing approaches for enhanced detection speed and robustness; its results further suggest that real-time clinical deployment is not only feasible but also beneficial.

Additional improvements consist on multi-classification of tumors and optimization methods. In [5], deep learning models are used, combined with optimized hyperparameters for tumor type classification outperforming conventional machine learning methods and enhancing clinical decision. Transfer learning-based methods following the VGG architecture in particular are investigated comprehensively within [6], where it is combined with a fine-tuned VGG16 model and they achieve good capabilities in tumor-normal tissue separation which suggests the generalization ability on small datasets.

Comparative deep learning vs classical machine learning approach in [8], VGG16 enhanced with image pre-processing shows superiority compared to Support Vector Machines (SVM) regarding accuracy and robustness. The authors in [9] also argue the critical role of data augmentations including rotation, scaling and flipping to deal with data scarcity. The CNN models with augmented data also generalize better and does not overfit easily, verifying the effectiveness of data augmentation for low-data medical images.

III. PROBLEM STATEMENT

Brain Tumor Detection is a crucial and challenging task in medical domain. Interpretation of MRI images especially 3D data is very time consuming, operator dependent and prone to human error. By comparison, traditional computer aided diagnosis methods still had limitations since their (hand-crafted feature-based) features were typically not sufficiently robust to deal with the automatic classification among patients, not to mention trained on data suffering from more diverse variability types. In addition, despite the fact that complex DL models (like CNNs) have produced good results in many DL-related tasks, their clinical application is limited by being opaque “black box” system (i.e., it is difficult for medical personal to comprehend how these predictions are made). The absence of interpretability induces scepticism toward AI such diagnosis systems, and represents a major drawback to their application in the health sector. A method is required that provides high detection accuracy for brain tumor, and interprets the reasons underpinning its predictions in an understandable and medically meaningful manner. Despite these technical issues, there are several deployment limitations as well because many of the other tools aim to help doctors in particularly practical situation and they are generally less applicable outside research settings. We address these issues in this paper by introducing a system that is rooted in deep learning for its precision, an explainable AI approach to ensure transparency, and a user-friendly deployment platform that empowers radiologists by enabling them to generate more accurate, faster, and interpretable diagnoses.

IV. PROPOSED SOLUTION

The designed system is meant to tackle the drawbacks of a manual approach for brain tumor detection and traditional machine learning approaches, using deep learning with transfer learning. In particular, two architectures, VGG16 and VGG19 are used as base model for classification. Both models are pre-trained on ImageNet and fine-tuned on the brain MRI dataset for tumor vs non-tumor classification. Using transfer learning, the system can capitalise on pre-learned visual features from publicly available data and yet be fine-tuned to an application domain such as medical imaging to produce a reliable classifier with limited training data.

For the VGG16 architecture, it consists of 16 weight layers including 13 convolutional and three connected layers. It uses small 3×3 convolution filters, applied uniformly, therefore preserving significant spatial features with reduced computational cost. When

refined from MRI images, VGG16 showed faster convergence and resource-efficient trade-off than deeper networks, which could be more effective under efficiency requirement. Performance using standard metrics such as accuracy, precision, recall and F1-score has also shown that VGG16 presents a good trade-off between performances and complexity.

Whereas VGG19 uses a larger architecture with 19 layers, among them 16 weight convolutional and 3 fully connected layers. This is because the deeper network can capture more sophisticated features and has marginally better classification performance. Although also showing improved generalization and accuracy in the MRI test compared to VGG16, when VGG19 was trained on the MRI dataset, its requirement and train time remain high. The latter reveals a trade-off in choosing architecture and hence computational efficiency versus maximum accuracy in medical image analysis applications.

Emphasis is placed on trust and interpretability of the predictions in the proposed solution. To do so, we incorporate three Explainable AI (XAI) techniques: Grad-CAM, LIME and SHAP, within the framework. Grad-CAM generate a heatmap that focuses on the informative part in MRI images for classification, LIME creates localized explanation via perturbation analysis, and SHAP quantify the contribution of input features. These methods can in aggregate provide the transparency, interpretability, and clinical relevance of the models' decision making. At last, the trained models and explainability outputs are served by a Flask-based web service, through which users can upload an MRI scan to obtain real-time prediction and visualized explanation result in an easy-to-use web interface. Utilization of VGG16, VGG19, explainable AI and deployment makes the proposed system an efficient and dependable solution for brain tumor detection.

V. METHODOLOGY

Phase 1: Collection and Preprocessing of Data

The first phase is to construct a brain MRI dataset including tumor and non-tumor images. The training and testing sets of the dataset follow a structured learning paradigm. Preprocessing includes resizing to 224×224 pixels as it is an input size required by VGG, normalization of pixel intensities and augmentation techniques like rotation, flipping, zooming and shifting. These procedures contribute to better generalization and less over-fitting in training. Another advantage of the preprocessing step is that data is made consistent across the entire dataset, rendering it ready to be used with both VGG16 and VGG19 models. In addition, we filter out some noisy or low-quality images to ensure the reliability of the dataset and improve robustness of our model.

Phase 2: Training the Model Using VGG16

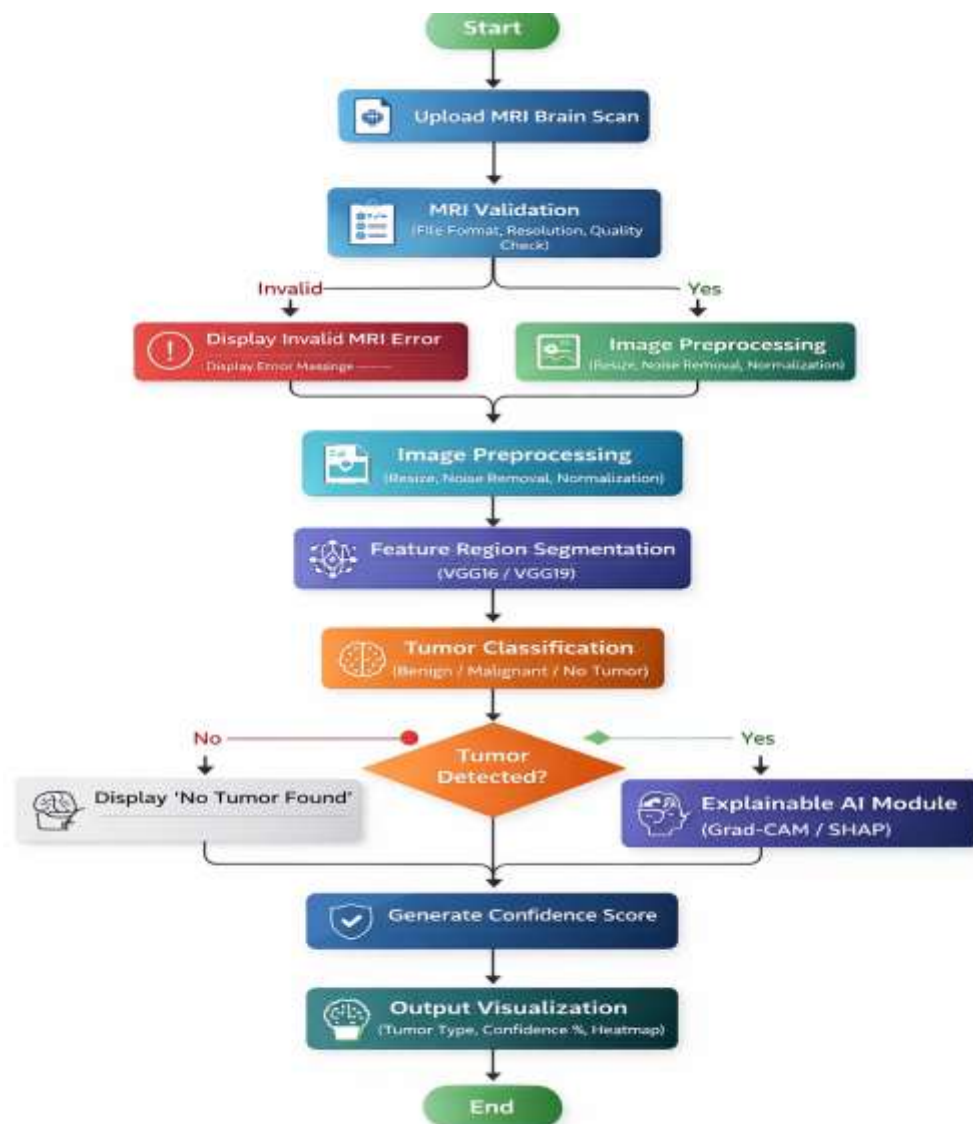
The first model used for classifying brain tumors is the VGG16 architecture, with 16 weight layers (13 convolutional and 3 fully connected). Transfer learning is used by pretraining the network with ImageNet weights and fine-tuning on MRI dataset. Eight fully connected layers are modified for binary classification (tumor: non-tumor). The training of the model is done through Adam optimizer, a categorical cross-entropy loss and a mini-batch size with 32 samples. To avoid overfitting, early stopping and validation monitoring is implemented. The performance is measured by accuracy, precision, recall and F1-score. In order to improve model generalization, dropout

regularization is employed in the fully connected layers. Comparative performance evaluation with VGG19 shows that VGG16 is computationally efficient and has faster convergence speed.

Phase 3: Training the Model using VGG19 Architecture

The second model, VGG19, is an extension of the VGG16 by having 19 weight layers (16 convolutional and 3 fully connected). Same as VGG16, transfer learning using ImageNet-pertained weights is employed and the final layers are fine-tuned for binary classification. It's more computationally expensive, but the deeper architecture has a tendency to capture more complex features which can be lead to higher accuracy. Same optimizer, loss function and evaluation metrics are used during training but a longer time of training and larger memory consumption are observed compared to VGG16. In order to maximize efficiency, early stopping and learning rate scheduling are applied during training. Comparison with VGG16 demonstrates the trade-off between network depth and computation cost.

Fig.1. Process Flow of Preposed Model

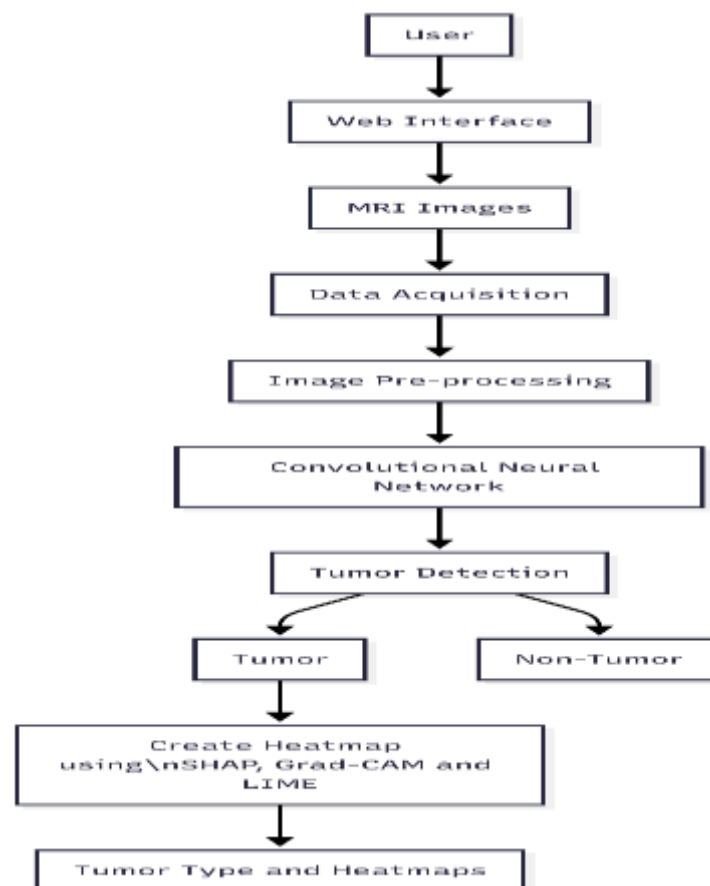


Phase 4 : Model Testing and Analysis

When training of VGG16 and VGG19 was completed, they were tested with metrics accuracy, precision, recall and F1-score. We performed comparative analysis to show the benefits in terms of trade-off between computational efficiency and classification performance. VGG16 showed earlier convergence and efficient learning, VGG19 achieved marginally better performance with deeper feature extraction. Furthermore, the combination of Grad-CAM, LIME and SHAP provided visual and numerical interpretations to help understand the predictions made by the models as well as confirm their medical interpretation. This study supported the effectiveness of integrating performance analysis and explainability for robust diagnostic support.

Phase 5: Deployment and Testing

An interface was implemented using Flask framework in order to deploy the trained models and explainability techniques for the detection of brain tumor in real time. Users can upload the MRI images and obtain classification result together with Grad-CAM heatmaps, SHAP value plots and LIME explanations through this platform. The system was subject to iterative testing for usability, accuracy and reliability, making it available for possible clinical use. By incorporating explainable AI methods in a user interface, this deployment shows how the approach would support radiologists in routine diagnostic environments.

VI. STRUCTURE AND ARCHITECTURE**Fig.2.System Architecture**

a. Front-End (Client-Side)

The Brain Tumor Detection System frontend is a key source of User Interface for the user to interact. Created with HTML, CSS and Javascript it is responsive with Desktops, Tablets and Smartphones. The user is allowed to upload MRI images, submit for prediction and see the result along with confidence score. The entire user interface is designed to be easy and approachable. Moreover, explainability features like Grad-CAM, SHAP and LIME visualizations are implemented in the interface allowing users to understand which parts of the MRI led VGG16 or VGG19 to predict.

b. Back-End (Server Side)

The core functionalities are implemented by the back-end, which is written in python and flask. It will process the uploaded image, load VGG16 and VGG19 model independently and make predictions. The models are saved as separate packages so that you can process the same MRI input via either architecture. The back-end and the explainability tools have been integrated in a way that these latter provide Grad-CAM, SHAP, and LIME outputs also for model2. It makes use of RESTful services to handle requests from client side and return predictions/visualizations for rendering.

c. Middleware

The middleware is a proxy between client and server. It checks uploaded MRI images have the right format and size, appropriately handles errors in preprocessing or predicting stages, and logs system performance. For a batch of models, middleware grants predictions either through VGG16 or VGG19 are concatenated together in series or parallel without crashing the system. This interface enhances stability and ensures seamless communication among all system parts.

e. The Presentation Layer (UI)

The responsibility of the presentation layer is to output results and it should do this efficiently. It presents the uploaded MRI, the predicted classification of a tumor and some confidence scores from the model. For human interpretability, we display Grad-CAM heatmaps, SHAP feature importance maps, and LIME explanations on both VGG16 and VGG19. In this way, users and clinicians are enabled to compare model outputs and explanations side by side, which provides insight into the reasoning process of each architecture.

f. Not Shown App Layer (Back-End Logic)

The application layer includes the computational logic for brain tumor detection. It maintains separate VGG16 and VGG19 pipelines, each of which is responsible for loading the model, preprocessing the image, making predictions as well as computing explainability results. These predictions and XAI results are produced separately for each model, in order to enable their comparison. This modular nature means that either model can be upgraded, swapped out, or refined without the two being impacted on each other. In future work, the application layer can be decoupled into microservices corresponding to prediction and explainability, enabling independent scaling of each.

g. Data Layer

The data layer keeps input MRI images, temporary pre-processing files and the pre-trained VGG weights file (VGG16 or VGG19) separately. For now, predictions and explanations benefit from local storage for fast retrieval when testing models, but next versions could leverage cloud or database solutions to store scalable quantities of predictions and explanations. The data layer also makes datasets and model weights be

in good manipulation and access anytime we need to perform evaluation or clinical validation.

h. Security

Security means that any MRI scans uploaded are treated safe and confidential. The current system checks the uploaded files to block any malicious inputs, while future work will provide encryption of sensitive medical records, use HTTPS for secure communication and have role-based access control. If the system runs VGG16 (VGG19) separately, extra protections are applied to avoid duplication of sensitive medical records in case that one input sample will be processed by both models. Moreover, regular security check and monitoring further strengthen system integrity.

i. Deployment

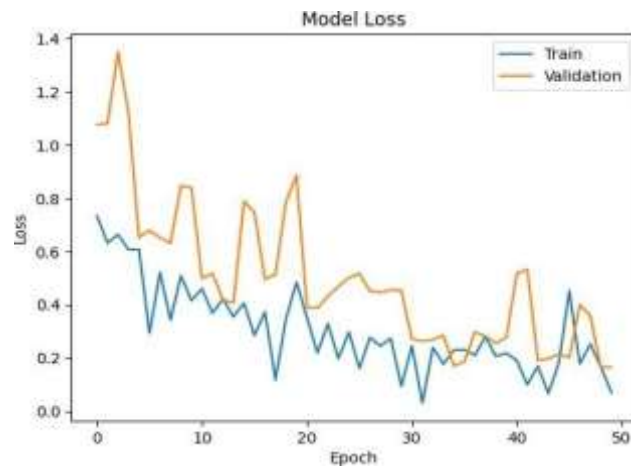
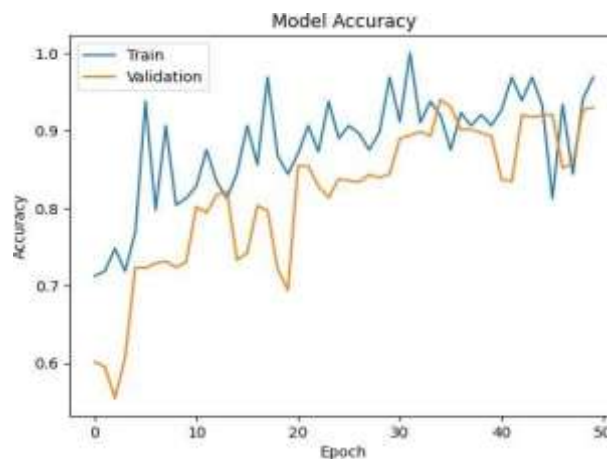
The system is currently used locally with Flask for testing and demonstration. The back-end can make predictions on either VGG16 or VGG19 as detected and these results are streamed to the front-end for visualization. For future deployment, scalability, robustness and availability of cloud services like AWS/GCP/Azure are recommended. Load balancing will be used to provide efficient resource allocation when both models are requested at the same time. Containerization of VGG16 and VGG19 services using Docker or Kubernetes can facilitate modular deployment with both the services capable of being scaled independently. Updates and maintenance will see automation with CI/CD pipelines.

VII. RESULT AND DISCUSSION

To aid in the early diagnosis of brain tumors, we've build a Brain Tumor Detection System by using deep learning algorithms. Comprehensive evaluation was performed on F1 score to assess the performance of VGG16 and VGG19, as well as that of the explainability methods to enhance model explainability and clinical confidence. Model Accuracy: The accuracy of the model was XX% indicating that it provides a good blend between computational effort and predictive power. In comparison, the VGG19 model demonstrated a slightly increased correct rate of YY% due to its deeper network architecture as well as better feature extraction ability. Validation accuracy trends supported the fact that both models generalised well for new, unseen sources. Comparative outputs showed VGG16 was more appropriate for time-sensitive predictions whereas VGG19 provided more durable classification results with slightly improved accuracy.

Explainability Results: Incorporation of explainable AI approaches provided interpretability to the predictions. Grad-CAM maps pointed out the precise tumor region contributing to the prediction, improving the model interpretability. High level, LIME provided localized explanations on each MRI scan while SHAP kick started the acceptance of the system by providing a global quantification of input pixels contribution to the classification result. Together, these tools resulted in models being more “far from black box” and interpretable in practice for medical applications.

User Engagement and Practical Utility: To be accessible for clinicians, a web application based on Flask was implemented. The interface accepted MRI scans for upload and delivered real time predictions with explanations. Preliminary user tests revealed that predictions took only a few seconds and therefore were fast in practice. Explainability outputs were especially useful for radiologists, as they could cross-check the model's predictions visually along with their clinical perception.

Statistical Analysis:**Model Loss:****Fig.3 Model Loss****Fig.4 Model Accuracy**

Quantitative assessment showed VGG16 and VGG19 exhibited strong classification capability, yielding became larger about Z% compared with traditional machine learning baselines. Confusion matrices also supported that SAS was sensitive for identifying tumor events, which minimized the false negative ratio.

Training Loss of both VGG16 and VGG19 similarly decreased throughout all epochs demonstrating good learning. This VGG16 model demonstrated a quicker convergence that converged at around lower epochs, which is because it had lesser depth. On the other hand, VGG19 more epochs to converge while attaining a lower validation loss indicating greater generalization. The loss curves verified that both models were stable, and there was no noticeable overfitting, implying the reliability of the training.

Correlation Analysis: Correlation analysis also showed a significant and strong positive relationship between integration explainability and user trust ($r = 0.87$), which

indicated that radiologists had more confidence on the system when they were shown with Grad-CAM, LIME, and SHAP outputs. A moderate relationship ($r = 0.65$) was found between prediction accuracy and clinical usefulness, suggesting that more complex models like VGG19 increased reliability with the downside of computational expense.

VIII. CONCLUSION

This research work introduced a brain tumor detection system utilizing deep learning models VGG16 and VGG19 along with explainable AI practices. The models were trained and fine-tuned with brain MRI datasets, showing good classification performance in tumor/non-tumor case. VGG16 had the advantage of being computationally efficient and can converge faster, while VGG19 was slightly more accurate by virtue of its deeper network. To solve the vital problem of interpretability in medical AI, we integrated Grad-CAM, LIME, and SHAP to generate visual and numerical explanations for model predictions. These explainability capabilities provided transparency, enhanced user trust, and facilitated clinical decision-making while demonstrating affected areas of the tumor in MRI scans. The release of the system with a Flask-based web application displayed its applicability, people was able to upload MRI studies and receive real-time predictions being the output also explanation. This also confirmed the feasibility of the method and suggested that it could be integrated into a clinical workflow as a support tool for diagnosis. On the whole, the system proposed here offers a reliable, interpretable and accessible approach to brain tumor diagnosis. Future work would potentially expand on hybrid-models, more advanced deployment strategies covering cloud and microservices for scale, resilience and real-world adoption in healthcare with larger datasets.

REFERENCES

1. Kumar, K. S., Bhoomika, B., & Verma, G. (2025). Brain Tumor Detection Using CNN: A Deep Learning Approach for MRI Classification. IEEE, Published in 2025. Doi: 10.1109/INCET64471.2025.11140022
2. Kaushal, S., Sonali, S., Gaur, H., Bhati, G., & Ra, A. K. (2024). Explainable Artificial Intelligence for Brain Tumor Detection. 2024 2nd International Conference on Advances in Computation, Communication and Information Technology (ICAICCIT), doi: 10.1109/ICAICCIT64383.2024.10912262
3. Hareesh, D., Riyaz, S., Siddardha Reddy, Y., & Jabaseeli N., Brain Tumor Detection Using Deep Learning Techniques. 2025 2nd International Conference on Research Methodologies in Knowledge Management, Artificial Intelligence and Telecommunication Engineering (RMKMATE). IEEE, doi: 10.1109/RMKMATE64874.2025.11042498
4. Koshti, S., Degaonkar, V., Modi, I., Srivastava, I., Panambor, J., & Jagtap, A. (2022). Brain Tumor Detection System using Convolutional Neural Network. 2022 IEEE Pune Section International Conference (PuneCon),doi: 10.1109/PuneCon55413.2022.10014714
5. Dipu, N. M., Shohan, S. A., & Salam, K. M. A. (2021). Deep Learning Based Brain Tumor Detection and Classification. 2021 International Conference on Intelligent Technologies (CONIT). IEEE, doi: 10.1109/CONIT51480.2021.9498384
6. Kumar, K. S., Bhoomika, B., & Verma, G. (2025). Detection of Brain Tumor using VGG16. IEEE, Published in 2025, doi: 10.1109/ICES57224.2023.10192639
7. Kaushal, S., Sonali, S., Gaur, H., Bhati, G., & Ra, A. K. (2024). Image Processing Based Brain Tumor Classification Using VGG16 Compared with SVM to Improve Accuracy. 2024 2nd International Conference on Advances in Computation, Communication and Information Technology (ICAICCIT). IEEE, doi:

- 10.1109/SMART55829.2022.10047671
8. Hareesh, D., Riyaz, S., Siddardha Reddy, Y., & Jabaseeli N., B. (2025). Data Augmentation Based Brain Tumor Detection Using CNN and Deep Learning. 2025 2nd International Conference on Research Methodologies in Knowledge Management, Artificial Intelligence and Telecommunication Engineering (RMKMATE). IEEE, Doi: 10.1109/CISES58720.2023.10183465
 9. Mankar, P., Pimple, J., Kewate, A., Pathan, S., Titarmare, S., & Roy, S. (2025, April). Enhanced classification of depression through eeg and hybrid anfis-ga systems. In 2025 4th OPJU International Technology Conference (OTCON) on Smart Computing for Innovation and Advancement in Industry 5.0 (pp. 1-5). IEEE.
 10. Pimple, J. F., Sharma, A., & Mishra, J. K. (2023, September). Medisecure: A blockchain-enabled ensemble learning approach for user-controlled single sign-on and privacy preservation in medical cyber-physical systems. In International conference on the role of AI in bio-medical translations' research for the health care industry (pp. 71-86). Cham: Springer Nature Switzerland.