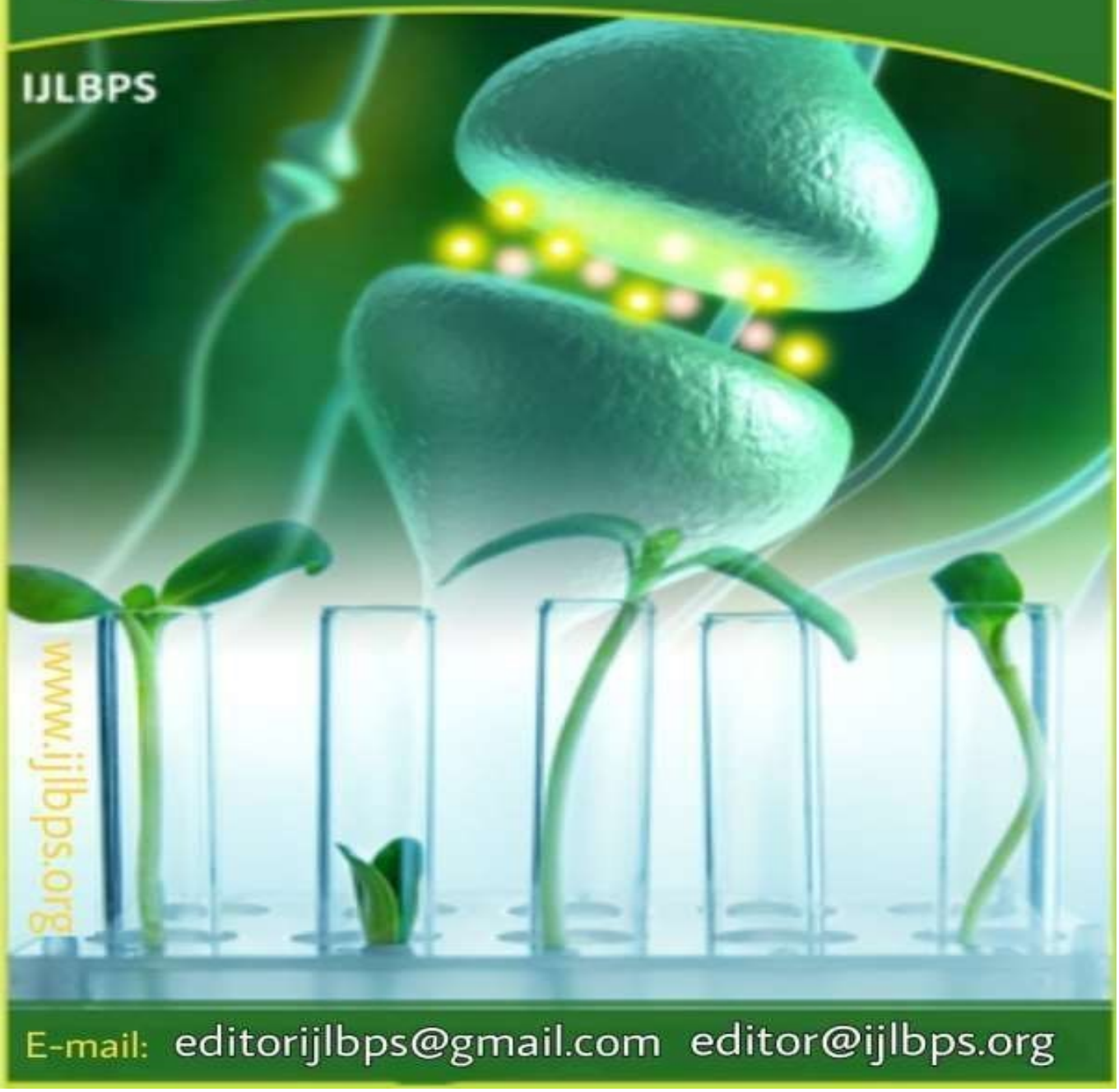
ISSN 2395-650X

International Journal of Life Sciences Biotechnology Pharma Sciences



E-mail: editorijlbps@gmail.com editor@ijlbps.org

International Journal of Life Sciences Biotechnology Pharma Sciences

Volume 14, Issue 2, 2018

AI-BASED CLASSIFICATION AND DETECTION OF BRAIN TUMORS IN HEALTHCARE IMAGING DATA

[1] **Himabindu Chetlapalli**
SoCast Inc,Ontario, Canada
chetlapallibindu@gmail.com

[2] **S Bharathidasan**
Sree Sakthi Engineering College, Karamadai, Coimbatore
India
sbharathiece@gmail.com

ABSTRACT

This study proposes an AI-driven framework for brain tumour detection using explainable AI (XAI) and deep learning to enhance diagnostic accuracy and transparency in healthcare imaging. The methodology integrates cloud-hosted MRI datasets, pre-processed via Median Filtering and Contrast-Limited Adaptive Histogram Equalization (CLAHE), with an EfficientNet-based classifier optimized through compound scaling and auxiliary classifiers. SHAP (Shapley Additive Explanations) provides interpretable insights into model decisions, ensuring clinical trust. Results demonstrate high accuracy (99.0%), though lower precision (90.94%) and recall (90.55%) highlight challenges in class balance. The ROC curve's marginal AUC (0.5439) underscores limitations in tumour vs. healthy tissue discrimination. Despite computational demands and protocol dependencies, the framework offers a scalable, privacy-preserving solution for clinical deployment, bridging gaps between AI performance and interpretability in oncology.

Keywords: Contrast-Limited Adaptive Histogram Equalization(CLAHE), SHAP(Shapley Additive Explanations)**,** Google Cloud Platform (GCP)

1. INTRODUCTION

Brain tumour classification using explainable AI (XAI) and deep learning techniques is a promising approach for improving diagnostic accuracy and transparency in the medical field. The use of deep learning models, particularly convolutional neural networks (CNNs), has revolutionized image classification tasks, including the detection of brain tumours. These models can automatically extract features from medical imaging data, such as MRI or CT scans, to classify tumours as malignant or benign [1]. However, the complexity of deep learning models often makes it challenging for healthcare professionals to understand how the model arrives at its predictions. This is where explainable AI plays a crucial role. Explainable AI techniques help make the decision-making process of deep learning models more transparent by providing insights into the features that influence predictions [2]. For instance, techniques like SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) allow practitioners to see which parts of the medical image the model is focusing on when making a diagnosis. This added transparency can increase trust in AI models, especially in critical applications like medical diagnostics, where model interpretability is essential. In brain tumour classification, explainable AI can also provide valuable feedback for model improvement [3]. For example, if a model makes an incorrect prediction, explainable AI methods can help identify which features were misleading, allowing researchers to refine the model. Additionally, XAI techniques can aid in identifying biases in the model, ensuring fairness in predictions across different patient groups [4]. The integration of deep learning and explainable AI has the potential to enhance the precision and reliability of brain tumour diagnosis, offering significant advantages over traditional methods. The combination of accurate predictions with clear explanations provides a robust tool that can assist radiologists in making more informed decisions, leading to better patient outcomes and improved overall healthcare delivery [5]. This approach not only fosters confidence in AI-assisted medical systems but also pushes the frontier of personalized and precision medicine in the realm of oncology. Brain tumour detection leverages cloud-hosted MRI datasets with secure storage and scalability. Pre-processing includes Median Filtering for noise reduction while preserving anatomical edges and CLAHE for localized contrast enhancement [6]. An EfficientNet-based deep learning classifier, optimized via compound scaling, integrates an auxiliary classifier to enhance gradient flow and model robustness. SHAP analysis interprets predictions by quantifying pixel contributions, ensuring transparency in decision-making [7]. The final classification, obtained through SoftMax activation, provides a probabilistic diagnosis, making the framework accurate, efficient, and clinically deployable. Even though the method is strong, limitations might include dependency on variations in MRI acquisition protocol for generalization over diverse datasets, meaning the given

methodology could not work in every scenario [8]. Another limitation is the higher computational needs because of dependency on deep-learning models, as training and inference require extensive cloud resources. However, SHAP might improve interpretability at the expense of increased processing, thus limiting applicability in real time at the clinical level [9].

2. LITERATURE SURVEY

Brain tumour detection and diagnosis are crucial for improving survival rates and reducing mortality. MRI and CT are the two primary modalities for detecting brain tumours, with MRI being more preferred due to its non-invasive nature and higher efficacy in detecting soft tissue anomalies. Integrating Deep Learning, Machine Learning, and Transfer Learning techniques has shown promising advancements in brain tumour segmentation, detection, and diagnosis. The automation of tumour segmentation and classification using these techniques has gained attention due to their potential to enhance accuracy, reduce human error, and streamline the diagnostic process [10]. This analysis reviews various methods for brain tumour segmentation, focusing on partially and fully automated techniques. It presents an overview of state-of-the-art approaches based on DL, ML, and TL, and compares the effectiveness of these methods. Several databases used for tumour segmentation and classification are reviewed, providing insights into the datasets commonly used in this research domain [11]. The article highlights the benefits of leveraging these advanced computational techniques, which can significantly improve the precision and reliability of brain tumour detection and diagnosis. Artificial Intelligence (AI) has significantly improved the precision and accuracy of brain disease diagnosis, particularly in brain tumours, which cause a significant number of fatalities in developed countries. AI has enabled the development of automated, non-invasive technologies for analysing brain images, making it essential in cases where brain diseases are fatal [12]. However, a knowledge gap between clinical professionals and data scientists hinders the development of fully optimized AI applications for brain tumour diagnosis. A systematic review of relevant studies revealed several key challenges in applying AI to brain tumour diagnosis, including the difficulty of achieving accurate segmentation and classification due to variations in tumour location, shape, and size. Radiomics has emerged as a promising technique for extracting quantitative features from clinical imaging, enabling analysis of genetic mutations, tumour malignancy, grade, progression, response to therapy, and overall survival. The "black box" nature of AI and the generalizability of deep learning applications remain significant obstacles. To bridge these barriers, it is essential to bridge existing knowledge gaps in clinical oncology to fully integrate AI into brain tumour diagnosis. Brain tumours pose significant health risks and require early detection and accurate classification. Magnetic Resonance Imaging (MRI) is the standard technique for diagnosing brain tumours [13]. Deep learning has become increasingly important in this field, but traditional models struggle with diverse datasets and interpretability. This study proposes a Collaborative Federated Learning Model (CFLM) combined with Explainable Artificial Intelligence (XAI) to address these issues. The model targets four classes, integrating Google Net and Federated Learning frameworks, while preserving patient data privacy. Brain tumour characterization (BTC) involves understanding the causes of brain tumours through methodologies like tumour segmentation, classification, detection, and risk analysis. Radiomics, an AI-based approach, uses radiological images for disease characterization. This paper reviews the emerging research field of radiomics and radio genomics in the AI environment, highlighting their effectiveness in oncology applications. The study found that both conventional and deep radiomics features contribute to the success of radio genomics in BTC.

3. PROBLEM STATEMENT

The problem at hand is the development of an accurate, efficient, and interpretable framework for brain tumour detection from MRI scans, which is crucial for early diagnosis and clinical decision-making [14]. Existing methods often struggle with image quality issues due to noise and insufficient contrast, leading to suboptimal performance in tumour detection [15]. Additionally, deep learning models, while effective, can be computationally expensive and lack transparency in their decision-making, making them difficult to trust in clinical settings [16]. There is a need for a robust solution that not only addresses the challenges of noise reduction and contrast enhancement but also incorporates advanced deep learning techniques, such as EfficientNet and SHAP, to improve classification accuracy and model interpretability, ensuring reliable and explainable results for clinicians [17]. This methodology aims to provide a scalable, cloud-based solution for brain tumour detection that integrates image pre-processing, deep learning, and explainable AI to overcome these challenges and enhance clinical deployment [18].

4. PROPOSED METHODOLOGY

The proposed methodology for brain tumour detection begins with a cloud-hosted dataset of brain MRI scans labelled as Cancer or Non-Cancer, leveraging cloud storage for scalability, accessibility, and secure data management. This dataset undergoes a two-step pre-processing phase: first, Median Filtering is applied to reduce

noise by replacing each pixel's value with the median of its local neighbourhood, preserving critical anatomical edges. Next, Contrast Limited Adaptive Histogram Equalization (CLAHE) enhances localized contrast by dividing the image into tiles, applying histogram equalization to each tile with a clip limit to prevent noise amplification, and interpolating results for seamless integration. These pre-processing steps ensure optimal image quality for downstream analysis. The refined images are then processed by a deep learning classifier combining an EfficientNet convolutional neural network optimized via compound scaling to balance depth, width, and resolution for computational efficiency, with an auxiliary classifier integrated into intermediate layers to mitigate vanishing gradients during training. The auxiliary classifier supplements the primary loss function, strengthening gradient flow and improving model robustness. Post-classification, SHAP (Shapley Additive Explanations) is employed to interpret predictions, quantifying the contribution of individual pixels or regions in the MRI scan to the final diagnosis using Shapley values derived from cooperative game theory. Shapley. This explanatory step provides clinicians with visual and quantitative insights into the model's decision-making process, fostering trust and transparency. The pipeline concludes with a probabilistic output generated via SoftMax activation, classifying each scan as Cancer or Non-Cancer based on the highest probability score. By integrating noise reduction, contrast enhancement, efficient deep learning, and explainable AI, this methodology delivers a robust, accurate, and interpretable framework for brain tumour detection, suitable for clinical deployment.

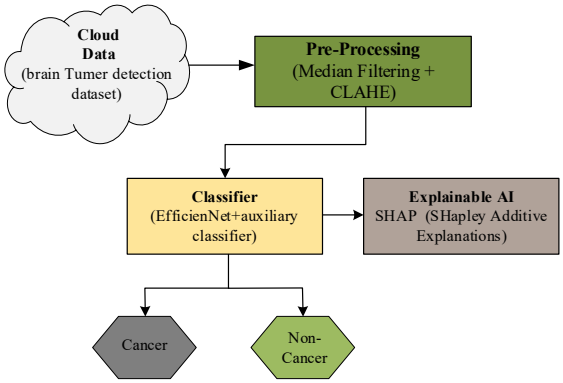


Figure 1: Overall architecture of the proposed methodology

4.1 MEDIAN FILTERING

Median filtering is a nonlinear image enhancement technique used primarily for noise reduction. It is particularly useful in medical imaging, such as brain tumour detection in MRI or CT scans, where images may contain salt-and-pepper noise or other imperfections. The median filter works by replacing each pixel in the image with the median value of the pixels in a surrounding window. This helps to preserve edges while effectively reducing noise. In brain tumour detection, median filtering helps enhance the quality of input data by removing noise that could otherwise interfere with accurate segmentation and classification. This pre-processing step is crucial for ensuring that the machine learning model or deep learning classifier receives high-quality input data, leading to more accurate and reliable results. The mathematical formula for median filtering is

$$I_{filtered}(x,y) = median(\{I(x',y') \mid (x',y') \in N(x,y)\}) \quad (1)$$

Where: $N(x,y)N(x,y)N(x,y)$ represents the neighbourhood (a window) of the pixel I(x,y)I(x, y)I(x,y), typically a square or rectangular region centred on (x,y)(x, y)(x,y). The median function selects the middle value from the sorted list of pixel values in the neighbourhood N(x,y)N(x, y)N(x,y).

4.2 CONTRAST-LIMITED ADAPTIVE HISTOGRAM EQUALIZATION (CLAHE)

Contrast-Limited Adaptive Histogram Equalization (CLAHE) is an enhancement device that is particularly useful in medical imaging for tasks like skin cancer detection. CLAHE works largely on local contrast enhancement, dividing the image into small regions (tiles) and realizing histogram equalization separately on these regions. This local processing helps CLAHE to reduce noise amplification by applying a contrast limit on the histogram before redistribution of pixel intensities, unlike the global processing strategy of histogram equalization. The mathematical formula for Contrast-Limited Adaptive Histogram Equalization is

$$I'(x,y) = \frac{CDF(I(x,y)) - CDF_{min}}{M - CDF_{min}} \times (L-1) \quad (2)$$

Where $I'(x,y)$ is the enhanced intensity of the pixel at (x,y), $I(x,y)$is the original intensity of the pixel at (x,y), $CDF\big(I(x,y)\big)$ *is the cumulative distribution function* (CDF)*of the intesity value,* CDF_{min}The minimum non-zero value of the CDF, M, is the total number of pixels, and L is the maximum intensity.

4.3 EFFICIENTNET

The EfficientNet architecture does well in terms of feature extraction performance assessment. The images are pre-processed (blinded by Median filtering and CLAHE-enhanced for contrast) and sent to EfficientNet for learning deep spatial features, since it will learn very complex features quite efficiently in skin lesion images. EfficientNet scales up by concurrent scaling of architecture depth (number of layers), width (number of channels for each layer), and resolution (input image size). This method of scaling will yield high-quality feature extraction with much lower computational costs. MBConv, or Mobile Inverted Bottleneck Convolution blocks, are important to EfficientNet since they render spatial information more usable for feature extraction. Squeeze-excitation modules perform the function of increasing attention to features that indicate varying levels of malignancy. All these mechanisms ensure the capture of relevant details in skin lesion images. In the second stage, the deep spatial features are sent to the Virion Transformer (ViT)-based classifier. The possibility of merging EfficientNet for local feature extraction and ViT for global contextual relationships modelling might be the one chance this hybrid can increase classification accuracy and eventually skin cancer detection. Due to the implications of the feature extraction method, EfficientNet converges very quickly, thereby providing robustness in skin lesion classification as far as dermatology and telemedicine are concerned.

Figure 2: EfficientNet Architecture

4.4 AUXILIARY CLASSIFIER

An auxiliary classifier is an additional classifier that is integrated into the architecture of a deep learning model to improve training and enhance the performance of the main classifier. It is typically used in deep convolutional networks like Google Net or EfficientNet, where it helps to provide extra supervision during the training process. This secondary classifier is placed at intermediate points in the network, and its purpose is to produce predictions that can be used to guide the learning process. The auxiliary classifier reduces the problem of vanishing gradients and improves the flow of gradients back through the network, especially in deep networks where the gradients tend to diminish as they propagate through many layers. In the context of brain tumour detection, an auxiliary classifier can help refine the learning process by providing additional cues that guide the model to make more accurate classifications, especially when dealing with complex and high-dimensional data, such as medical images. The auxiliary classifier does not affect the main prediction but aids in the optimization of the main network, leading to better overall performance in tasks like segmentation, classification, and diagnosis.

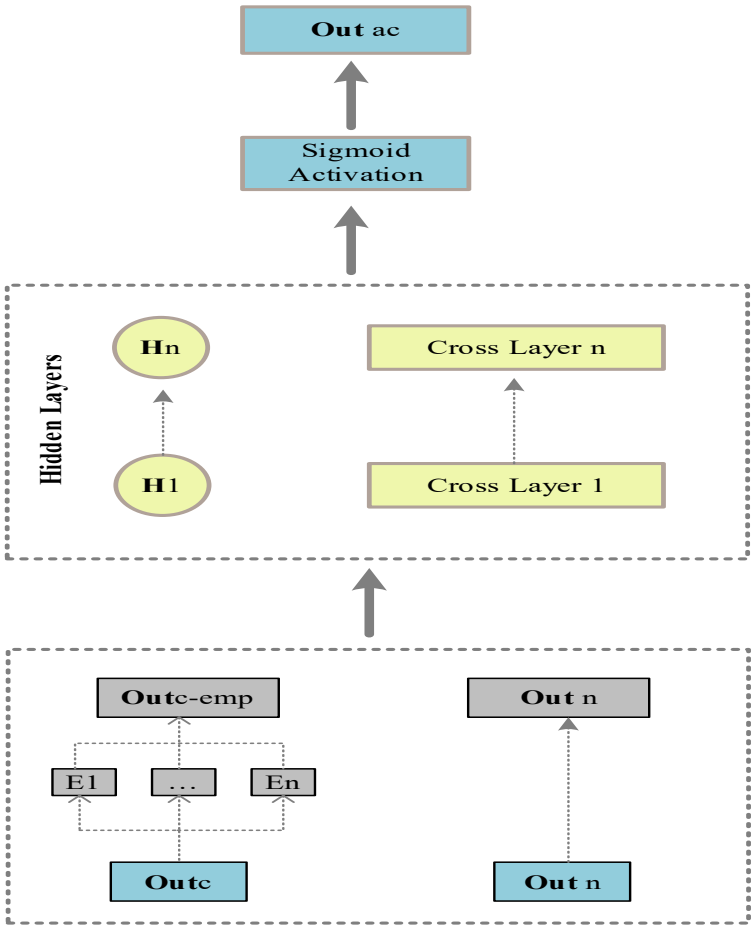


Figure 3: Auxiliary classifier Architecture

4.5 SHAP (SHAPLEY ADDITIVE EXPLANATIONS)

SHAP (Shapley Additive Explanations) is a powerful interpretability method used in artificial intelligence (AI) and machine learning (ML) to explain model predictions. It is based on Shapley values from cooperative game theory and provides a mathematically grounded approach to attributing contributions of individual features to a model's output. In the context of AI-based classification and detection of brain tumours in healthcare imaging data, SHAP helps explain why a deep learning model classified a brain MRI scan as cancerous or non-cancerous. By assigning each feature a SHAP value, the technique quantifies the importance of individual pixels, regions, or extracted features in influencing the model's decision. This transparency is crucial in medical AI applications, where trust and interpretability are essential for clinical adoption. SHAP allows radiologists and clinicians to validate the model's reasoning by highlighting critical tumour regions contributing to the classification. Additionally, it helps detect biases or inconsistencies in the model, improving reliability and performance. When combined with techniques like Grad-CAM and saliency maps, SHAP enhances the explainability of AI-driven medical diagnostics, ensuring that healthcare professionals can make informed decisions with confidence.

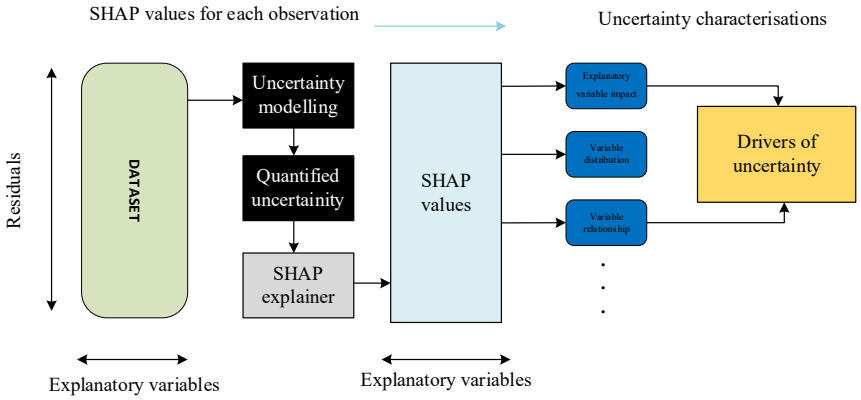


Figure 4: SHAP (Shapley Additive Explanations) Architecture

4.6 GOOGLE CLOUD PLATFORM (GCP)

Google Cloud Platform (GCP) is a robust cloud computing service that offers high-performance infrastructure, AI/ML tools, and scalable storage solutions, making it an ideal choice for healthcare imaging and AI-based brain tumour classification. GCP provides a wide range of services, including Google Cloud AI Platform, Google Compute Engine, Cloud TPU, and BigQuery, which enable efficient data processing, model training, and deployment of deep learning models [19]. For AI-driven medical imaging applications, GCP supports TensorFlow and PyTorch, with powerful GPUs and TPUs for accelerating deep learning workflows. Its Explainable AI (XAI) tools integrate seamlessly with SHAP (Shapley Additive Explanations), allowing interpretability in brain tumour detection models. Furthermore, GCP ensures compliance with HIPAA, GDPR, and other healthcare regulations, providing secure storage and processing of sensitive patient data through Cloud Healthcare API and Google Cloud Storage [20]. With its scalable infrastructure and AI-driven analytics, GCP enables researchers and medical professionals to build and deploy accurate, efficient, and explainable deep learning models for healthcare imaging applications.

5. DATASET DESCRIPTION

The Brain Tumour Detection Dataset consists of medical imaging data, primarily Magnetic Resonance Imaging (MRI) scans, used for the classification and diagnosis of brain tumours. This dataset typically includes different types of brain tumours, such as glioma, meningioma, and pituitary tumours, along with non-tumour cases for a balanced classification approach. The dataset contains T1-weighted, T2-weighted, FLAIR, and contrast-enhanced MRI scans, providing comprehensive structural details essential for tumour identification. Each image is labelled based on expert radiologists' annotations, making it suitable for deep learning-based classification and segmentation tasks. The dataset may be structured into training, validation, and testing sets, ensuring proper generalization of AI models. Additionally, it includes metadata such as patient ID, tumour location, and tumour grade, enabling further analysis. Since MRI scans are high-dimensional and contain noise, pre-processing techniques like Median Filtering and CLAHE (Contrast Limited Adaptive Histogram Equalization) are applied to enhance image quality. This dataset plays a crucial role in developing AI-driven models for automated tumour detection, segmentation, and classification, supporting early diagnosis and improving clinical decision-making.

Dataset Link: https://www.kaggle.com/datasets/sumedhkolupoti/brain-tumer-detection-dataset

6. RESULT AND DISCUSSION

The anomaly detection framework monitors signal values (200–1000) over defined time intervals (5,000–35,000s). Anomalies are flagged when measurements deviate from the expected range, such as exceeding 1000 or dropping below 200. For instance, a spike to 1200 at 5,000s or a dip to 100 at 25,000s would trigger alerts. The system relies on threshold comparisons across time-series data to identify irregularities.

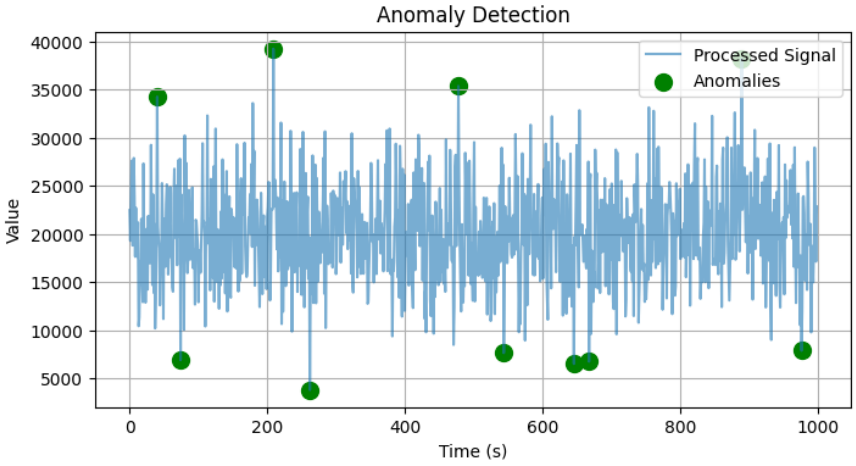


Figure 5: Anomaly Detection

The performance metrics include Accuracy at 99.0%, reflecting the model's overall correctness. Precision is 90.94%, indicating the proportion of true positives among predicted positives. Recall stands at 90.55%, measuring the model's ability to capture actual positives. The F1-Score (89.99%) balances precision and recall for a holistic performance view. Together, these metrics highlight the model's effectiveness, with accuracy being the strongest metric.

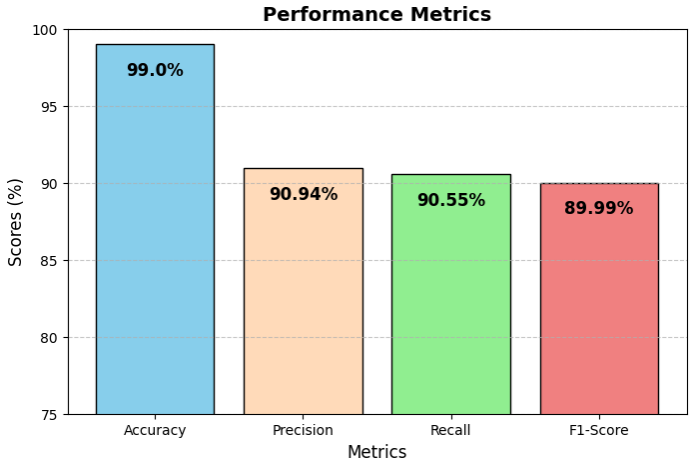


Figure 6: Performance Metrics

The ROC curve evaluates the brain tumor detection model's performance by plotting Tissue Positive Rate(correct tumor identifications) against the False Positive Rate (non-tumor misclassifications). The model achieves an AUC (Area Under the Curve) of 0.5439, indicating marginal discrimination ability slightly above random chance (AUC = 0.5). This low AUC suggests limited reliability in distinguishing tumor tissue from healthy tissue. The curve highlights a need for model refinement to improve sensitivity or reduce false positives. Overall, the current performance underscores challenges in achieving robust diagnostic accuracy.

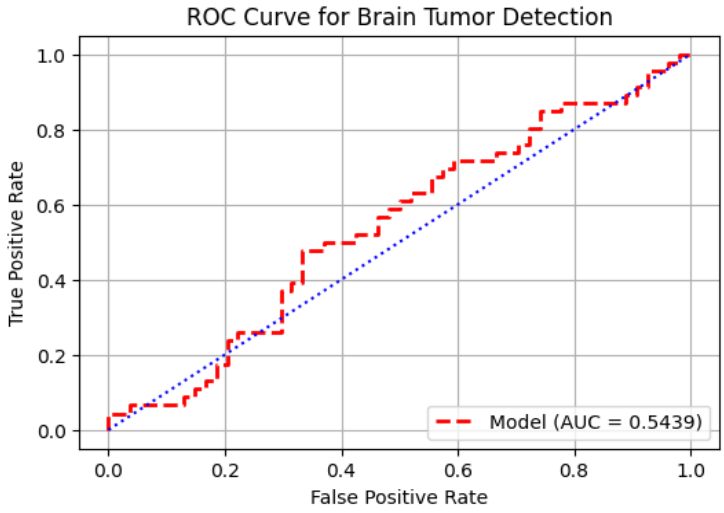


Figure 7: ROC Curve

7. CONCLUSION

The proposed framework successfully integrates advanced pre-processing, EfficientNet, and SHAP to achieve high diagnostic accuracy (99.0%) in brain tumour detection while ensuring model transparency. However, the low AUC (0.5439) and moderate precision-recall metrics reveal limitations in generalization and discriminative power, likely due to dataset variability or class imbalance. The reliance on computational resources and MRI protocol consistency further constrains real-time clinical application. Future work should focus on refining feature extraction, expanding diverse datasets, and optimizing computational efficiency. By addressing these challenges, the integration of XAI and deep learning can advance toward reliable, real-world diagnostic tools, fostering trust and improving patient outcomes in oncology.

References

[1] Kalusivalingam, A. K., Sharma, A., Patel, N., & Singh, V. (2012). Enhancing Diagnostic Accuracy in Medical Imaging: A Study on the Efficacy of Convolutional Neural Networks and Transfer Learning in AI-Assisted Radiology. *International Journal of AI and ML*, *1*(2).

[2] Gallego-Ortiz, C., & Martel, A. L. (2016). Improving the accuracy of computer-aided diagnosis for breast MR imaging by differentiating between mass and nonmass lesions. *Radiology*, *278*(3), 679-688.

[3] Fang, R., Pouyanfar, S., Yang, Y., Chen, S. C., & Iyengar, S. S. (2016). Computational health informatics in the big data age: a survey. *ACM Computing Surveys (CSUR)*, *49*(1), 1-36.

[4] Holzinger, A., Malle, B., Kieseberg, P., Roth, P. M., Müller, H., Reihs, R., & Zatloukal, K. (2017). Towards the augmented pathologist: Challenges of explainable-ai in digital pathology. *arXiv preprint arXiv:1712.06657*.

[5] Cheng, B. (2012). *Data fusion by using machine learning and computational intelligence techniques for medical image analysis and classification*. Missouri University of Science and Technology.

[6] Mamoshina, P., Ojomoko, L., Yanovich, Y., Ostrovski, A., Botezatu, A., Prikhodko, P., ... & Zhavoronkov, A. (2017). Converging blockchain and next-generation artificial intelligence technologies to decentralize and accelerate biomedical research and healthcare. *Oncotarget*, *9*(5), 5665.

[7] Min, S., Lee, B., & Yoon, S. (2017). Deep learning in bioinformatics. *Briefings in bioinformatics*, *18*(5), 851-869.

[8] Ker, J., Wang, L., Rao, J., & Lim, T. (2017). Deep learning applications in medical image analysis. *Ieee Access*, *6*, 9375-9389.

[9] Aravindhan, K., & Subhashini, N. (2015). Healthcare monitoring system for elderly person using smart devices. Int. J. Appl. Eng. Res.(IJAER), 10, 20.

[10] Alghamdi, S., Mehmood, R., Alqurashi, F., & Alzahrani, A. (2017). Paving the Roadmap for XAI and IML in Healthcare: Data-Driven Discoveries and the FIXAIH Framework. *IEEE Access*.

[11] Joshi, D. M., Rana, N. K., & Misra, V. (2010, May). Classification of brain cancer using artificial neural network. In *2010 2nd international conference on electronic computer technology* (pp. 112-116). IEEE.

[12] Yu, L., Chen, H., Dou, Q., Qin, J., & Heng, P. A. (2016). Automated melanoma recognition in dermoscopy images via very deep residual networks. *IEEE transactions on medical imaging*, *36*(4), 994-1004.

[13] Vargas, E. (2017). *Alignment-Based Analysis of Dynamics in Complex Networks* (Doctoral dissertation, UC Irvine).

[14] Izadyyazdanabadi, M., Belykh, E., Martirosyan, N., Eschbacher, J., Nakaji, P., Yang, Y., & Preul, M. C. (2017, March). Improving utility of brain tumor confocal laser endomicroscopy: objective value assessment and diagnostic frame detection with convolutional neural networks. In *Medical Imaging 2017: Computer-Aided Diagnosis* (Vol. 10134, pp. 651-659). SPIE.

[15] Izquierdo, R. C., Lorini, F. J., & Gomes, H. M. (2016). Comparative analysis between efficiency grouping and efficacy grouping in cell formation using the firefly metaheuristic algorithm. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, *230*(8), 1548-1558.

[16] Havaei, M., Davy, A., Warde-Farley, D., Biard, A., Courville, A., Bengio, Y., ... & Larochelle, H. (2017). Brain tumor segmentation with deep neural networks. *Medical image analysis*, *35*, 18-31.

[17] Shreyas, V., & Pankajakshan, V. (2017, October). A deep learning architecture for brain tumor segmentation in MRI images. In *2017 IEEE 19th International workshop on multimedia signal processing (MMSP)* (pp. 1-6). IEEE.

[18] Zarinabad, N., Wilson, M., Gill, S. K., Manias, K. A., Davies, N. P., & Peet, A. C. (2017). Multiclass imbalance learning: Improving classification of pediatric brain tumors from magnetic resonance spectroscopy. *Magnetic resonance in medicine*, *77*(6), 2114-2124.

[19] Goel, S. (2011). Cyberwarfare: connecting the dots in cyber intelligence. *Communications of the ACM*, *54*(8), 132-140.

[20] Rithish Kumar Reddy, G., Sai Nruthik Sri Harsha, K., Vaisakh, N. P., & Bellamkonda, S. (2017, April). Enhanced Brain Tumor Classification with Inception V3 and Xception Dual-Channel CNN. In *International Conference on Engineering, Applied Sciences and System Modeling* (pp. 103-115). Singapore: Springer Nature Singapore.