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Optimizing brain tumor classification with hybrid CNN architecture: Balancing accuracy and efficiency through oneAPI optimization

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ABSTRACT

A brain tumour is a malignant condition that spreads extremely quickly and requires rapid detection. In recent years, it has become apparent that deep learning is a promising technique for classifying brain tumours. To identify these tumours, this work proposes a hybrid CNN architecture, implementing InceptionV3, ResNet-50, VGG16, and DenseNet. To evaluate this approach, a total of 3929 images was obtained from Kaggle, including 2556 non-tumorigenic and 1373 tumorigenic specimens. Initially, the method extracts features from MRI pictures, then segments the tumour using the mask images. Subsequently, the segmented tumour image is fused with the original image, and finally the fused image is classified with the assistance of four distinct CNN models, specifically InceptionV3, ResNet, DenseNet, and VGG16. To enhance the performance of the hybrid architecture, these models were further optimized with oneAPI, which allows a comparative analysis of each individual model for classification. To evaluate the effectiveness of medical image classification models, a variety of evaluation criteria have been utilized extensively. We highlight the use of mean Intersection over Union (mIoU) as a more acceptable and intuitive statistic for evaluating the balance between true positives, false positives, and false negatives. This is in response to recent breakthroughs that have been made.

1. Introduction

Brain tumours are a serious form of cancer that pose a considerable risk to the patient's life and impact a significant number of people all over the world. It is essential to accurately diagnose brain tumours to plan for therapy effectively, monitor the condition's progression, and classify and localize any existing tumours [1]. The early stages of brain tumour diagnosis are notoriously challenging since diagnostic tools are unable to obtain an exact tumour measurement [2]. However, if the brain tumour is diagnosed, doctors can begin the appropriate treatment, increasing the patient's survival and recovery outcome. Depending on the tumour, therapies may include chemotherapy, radiation therapy, and surgery [3]. The diagnosis of brain tumours can be fairly challenging due to their widely varying forms, sizes, locations, and appearances. The medical imaging method utilized in diagnosing cancer plays a significant part in resolving diagnostic issues; the reliability of the architecture depends on the clarity of the visualization and the quality of the results. Because of its capacity to offer specific structural information, Magnetic Resonance Imaging (MRI) has recently gained popularity as a strong imaging tool for examining brain tumours [4]. Complex DNNs are black boxes that hide why and how a model made a decision [5]. The lack of interpretability in decision-making processes hampers physicians and researchers who need transparency and explanations to accept and validate the DL system's results. Researchers have turned to explainable artificial intelligence (XAI) to overcome the black box issue. XAI attempts to address the complexity of DL models and the necessity for interpretable decision-making [6]. Various tools and methodologies are used to provide insights and explanations for DL model predictions. Recent years have seen significant development and increased use of Convolutional Neural Networks (CNNs), particularly in

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the realm of medical image categorization CNN models have the ability to automatically learn features from the input images. Despite the fact that these models are typically effective, there is a challenge involved in properly finding the tumours. To provide better-focused treatment planning and surgical treatments, it is necessary to locate the precise region of the tumour. In this study, a unique CNN architecture is proposed with the purpose of resolving the issues of the current brain tumour classification methods. Our dataset, comprising 3929 images was curated from the TCGA LGG collection [7], which was sourced from five separate institutions. These institutions are Thomas Jefferson University, Henry Ford Hospital, the University of North Carolina, Case Western, and Case Western – St. Joseph's. Notably, all images in the dataset are available in the. tif (Tagged Image File) format. The choice of this format was deliberate, considering its suitability for maintaining high-quality imaging data, which is crucial for the performance of our deep learning model. The dataset consists of 2556 images classified as non-tumorigenic and 1373 images classified as tumorigenic.

To mitigate the problem of class imbalance, an approach including the use of both oversampling and undersampling was employed. Specifically, the tumorigenic class was oversampled, while the non-tumorigenic class was undersampled to balance both the classes. The selection of external datasets that represented a wide range of demographics, imaging techniques, and equipment was done to assess our findings' generalizability. A more realistic portrayal of the obstacles that the model would face in a variety of clinical situations is provided by the inclusion of datasets from several institutions, which adds an additional layer of complexity to the evaluation. In the developed CNN architecture, the characteristics are first retrieved, then the mask images are utilized to segment various parts of the tumour. When combined with MRI images, the tumour regions that were previously segmented produce a classification model that is both more robust and accurate equipped with explainable AI to enhance interpretability. The remaining portions of this paper are structured as follows. Section 2 provides a summary of relevant works in the categorization of brain tumours using CNNs. Section 3 discusses the entire process, including the suggested CNN architecture and optimization with oneAPI and models it supports. The results and discussion are described in Section 4. The conclusion and future steps are provided in Section 5.

2. Literature survey

In past research [8], a deep residual learning framework was built for the purpose of classifying MRI images of brain tumours. Without requiring human input, the suggested ResNet model uses an evolutionary method to automatically assign hyperparameters. Using this technique, an average accuracy rate of 98.6 % was achieved. In another study [9], the researchers constructed a model named MobileNetV1 to identify brain cancers, which was evaluated based on four primary metrics. Impressive results showed that the model achieved an accuracy of 97 %. Deep CNN was employed with dimension scaling for image quality, depth of layers, and breadth of channels in the DCNNBT model in Ref. [10] This model was used in conjunction with rigorous optimization of the hyperparameters and attained an accuracy of 99.18 %. In Ref. [11], a GAN deep learning technique was proposed, which achieved an accuracy of 96 %. The technique applies CNN to construct the generator and a deconvolutional neural network as the discriminator. The CE-MRI dataset was utilized for the purpose of this study. Using InceptionV3 and EfficientNet-B2, the authors of [12] built an improved classification system for brain tumours. Results revealed an accuracy of 78 % for InceptionV3 and 76 % for EfficientNet-B2. The authors of [13] applied an innovative approach to extract and categorize tumour characteristics in 3D brain slice pictures. Specifically, they developed an approach for the extraction and classification of features of brain tumours utilizing deformable models combined with DL techniques. The proposed method uses of a Deformable Hierarchical Heuristic Model-Deep Deconvolutional Residual Network (DHHM-DDRN) and

Table 1
A detailed comparison of other existing works.

Ref	Year	Model	*Result (Validation Merits Accuracy)*	Inference	Validation Accuracy of Proposed Hybrid CNN Architecture Models
[16]	2021	VGG-16	90 %	VGG16 is used for feature extraction, which can efficiently perform and, through transfer learning, provides additional features as input to an artificial neural network classifier. The proposed model known as the Binary Classifier assigns a value of either 0 (indicating that there is no tumour) or 1 (indicating that a tumour does exist) to each of the input images.	91.04 %
[17]	2022	ResNet-50	79.32 %	This study made an effort to automate the diagnosis process such that manual steps are no longer necessary. Instead, the proposed method relies on machine learning. CNNs that have already been trained on data have been suggested as a method for diagnosing and classifying brain cancers. One class of non-tumour MRI images was used to classify each of the three different types of cancers.	95.5 %
[18]	2021	InceptionV3	61.78 %	In order to accomplish binary classification, three different architectures (VGG-16, Inceptionv3, and Xception) based on transfer learning were tested.	71.54 %

(*continued on next page*)

Table 1 (*continued*)

Ref	Year	Model	*Result (Validation Merits Accuracy)*	Inference	Validation Accuracy of Proposed Hybrid CNN Architecture Models
				Accuracy was used to determine the best results.	
[19]	2021	DenseNet	88.00 %	The proposed technique can detect brain cancers with a high degree of accuracy; yet, there are still limitations to the procedures. Deep learning and transfer learning are discussed in this paper as they relate to the categorization of MRI-based classification of brain cancers. Transfer learning makes it possible to incorporate a wide variety of domains, functions, and distributions into instruction and study.	94.65 %
[20]	2023	ResNet-50	91.56 %	In order to identify brain tumours using magnetic resonance imaging (MRI) pictures, the purpose of this study evaluates three deep learning tools: VGG-16 ResNet50 and AlexNet.	95.5 %
[21]	2023	Vgg16	88 %	The investigation into the detection of brain tumours through the utilization of the VGG-16 model, a convolutional neural network well-known for its effectiveness in computer vision applications. In order to correctly identify the existence of brain tumours, the purpose of the study is to classify images obtained by magnetic resonance imaging (MRI techniques). MRI scans of brain tumours are included in the dataset that was utilized. These pictures were classified into two distinct groups: "NO" (no tumour) and "YES" (tumour). Establishing the environment, then importing and preparing the data, and finally constructing the VGG-16 model are all components of the methodology.	91.04%

achieved an accuracy of 95 %. Table 1 presents a comparison of several different CNN models, such as InceptionV3, ResNet, DenseNet, and VGG16, used in other similar works. This study was conducted to evaluate these models' performance in accurately identifying the combined images and differences between the proposed architecture and existing conventional models. The proposed method is inferred to outperform the conventional models as a classification system with greater reliability and higher accuracy. Researchers in Ref. [14] have devised a way to fix the problem that non-Euclidean distances in image data are not taken into account and that regular models cannot learn about pixel similarity based on how close two pixels are to each other. The study introduced a novel Graph-based Convolutional Neural Network (GCNN) model. A total of five distinct networks, specifically Net-0, Net-1, Net-2, Net-3, and Net-4, were developed and evaluated. The results indicate that Net-2 exhibited superior performance compared to the other networks. Net-2 achieved the highest level of accuracy, reaching 95.01 %. The study [15] devised an innovative convolutional neural network (CNN) structure. The performance assessment of classifying three unique types of brain tumours involved the utilization of two ten-fold cross-validation techniques. The model's accuracy was determined by applying it to a record-wise cross-validation dataset, resulting in a rating of 92.50 %.

In this work, a hybrid CNN architecture is proposed to increase the overall accuracy presented in Table 2 and the reliability of other conventional models used in other works.

3. Proposed solution

The proposed novel CNN architecture for brain tumour classification includes image fusion with several CNN models. As input, the architecture requires an MRI image of a brain tumour and the image of tumour without the surrounding tissue. In order to extract features from the MRI images, four different CNN models, namely InceptionV3, ResNet, DenseNet, and VGG16, are used. For the purpose of capturing broad visual representations, these models were pretrained on a massive

Table 2
Comparison of metrics of our proposed models.

S: No	Models	Validation Accuracy (mean ± std. deviation)	Precision (mean ± std. deviation)	Recall (mean ± std. deviation)	F1-Score (mean ± std. deviation)	Sensitivity (mean ± std. deviation)	mIou	Specificity (mean ± std. deviation)
1	ResNet-50	95.5 ± 0.3	92.5 ± 1.0	93.5 ± 0.8	93.0 ± 0.5	0.92 ± 0.03	93.6	0.89 ± 0.02
2	VGG16	91.04 ± 0.6	88.2 ± 0.9	90.5 ± 0.7	89.3 ± 0.4	0.87 ± 0.02	89.3	0.85 ± 0.03
3	InceptionV3	71.54 ± 1.2	65.8 ± 1.5	78.2 ± 2.0	71.5 ± 1.3	0.78 ± 0.02	71.8	0.72 ± 0.03
4	DenseNet	94.65 ± 0.4	91.9 ± 0.7	94.2 ± 0.6	93.0 ± 0.4	0.93 ± 0.02	93.0	0.90 ± 0.01

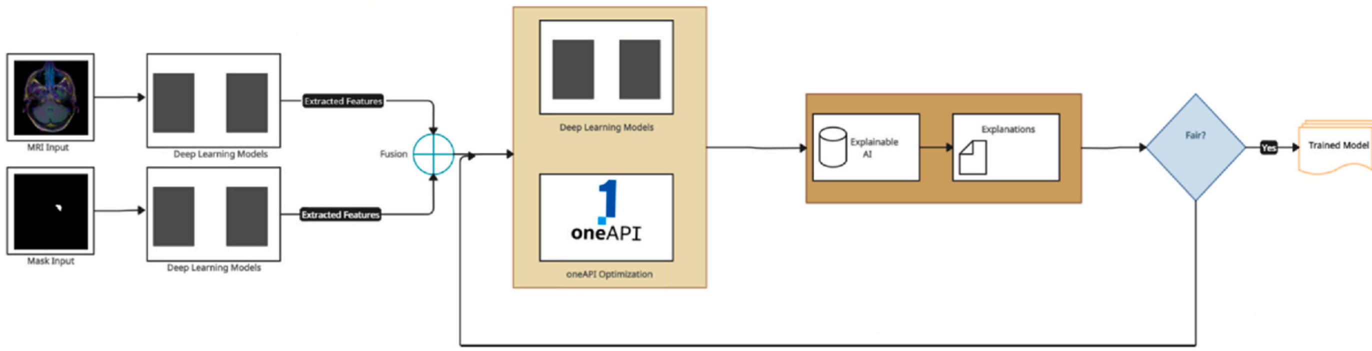

Fig. 1. Proposed novel architecture for classifying brain tumours.

dataset. The CNN models are applied to the MRI images and processed in order to extract high-level characteristics. In parallel, the mask pictures are utilized for segmentation to locate the regions affected by the tumour precisely. A careful mask image generation method is employed to find tumour areas with great accuracy. The MRI pictures are first preprocessed using the proposed method to ensure consistent quality. Then, the U-Net architecture is a convolutional neural network made for image segmentation and generating masks. After the tumour regions have been segmented, they are combined with the initial MRI pictures to create fused images [22]. These fused images maintain the anatomical details and information about the tumour's location. After that, the fused pictures are identified by utilizing the four different CNN models, which enables a comparison analysis of how well they can identify brain tumours. The XAI layer utilizes these comparisons to explain the deep learning model's predictions. The cloud storage of the trained model is determined by whether or not the explanations that are offered by the XAI layer are regarded as sufficient, which indicates that the logic behind the predictions is fair. On the other hand, if the explanations are regarded insufficient, the model then goes through retraining to enhance its performance. The suggested architecture integrates feature extraction, tumour segmentation, image fusion, and several CNN models in an effort to increase the accuracy and resilience of brain tumour classification. Four convolutional neural network (CNN) models, namely InceptionV3, ResNet, DenseNet, and VGG16, were considered in this work as they are recognized for their efficacy in optimizing deep neural networks. We employed a standardized set of hyperparameters for these models to ensure equitable and comparable evaluations and applied the Adam optimizer with default configurations. To address the issue of overfitting and improve the ability of the models to generalize, a consistent dropout rate of 0.5 was used. The dropout rate implemented in the training process resulted in the deactivation of around 50 % of neurons, hence minimizing excessive dependence on specific features and facilitating improved generalization to unfamiliar data. The selection of these standardized hyperparameters was informed by established principles in deep learning and tailored to meet the specific demands of our brain tumour classification assignment, ensuring uniformity in our model assessments. Fig. 1 illustrates the proposed architecture.

3.1. Ethical considerations in dataset usage

By utilizing an open dataset collected from the internet for this research, we demonstrate our dedication to adhering to ethical norms while dealing with the data provided. In compliance with the permissions and terms of use that the creators of the dataset stated, we received the dataset from TCGA LGG collection. We recognize the efforts that were made by the original data sources, and we are committed to making responsible use of the data going forward. Despite the fact that we do not have any direct interactions with individual patients, we are aware of the significance of privacy concerns and have taken steps to anonymize any personally identifying information that may be contained within the dataset. Without compromising the scientific validity of the dataset, our processes were designed to prevent the identification of specific individuals who participated in the study. We promote transparency in our data usage by providing detailed documentation on the source of the dataset, its characteristics, and any modifications made for our research. With this strategy, we ensure that our study is in accordance with acceptable research procedures, which in turn helps to create trust and transparency in our utilization of the dataset that is freely accessible to the public.

3.2. Deep learning models

Four models are used as feature extractors in the proposed architecture. The tumours are classified based on the characteristics extracted from the data. In addition, the fused images produced from the image fusion stage are entered into each of the four CNN models separately to classify the tumour.

i) VGG16

Visual Geometry Group 16 (VGG16) is a CNN design that was presented by the Visual Geometry Group at the University of Oxford in 2014. As a result of its deeply layered architecture, it is widely used for various computer vision functions, such as the segmentation, classification, and object detection of images [23]. In the VGG16 network in the proposed architecture implements convolution layers with a 3×3 filter and a stride 1 and maintains the same padding and max-pool layers with a 2×2 filter and a stride 2. This configuration of convolution and max pool layers is maintained in a consistent manner throughout the entirety of the architecture. In the end, it consists of two totally coupled layers, followed by a SoftMax as the output [24]. The number 16 in VGG16 is a reference to the fact that it contains 16 layers with weights. The size of this network is rather impressive, as it contains over 138 million parameters [25]. Equation (1) represents the Convolutional Layer, and Equation (2) represents the Fully Connected Layer where Y is the output. X is the input, W is the weight matrix,b is the bias vector,* denotes the convolution operation, σ is the ReLU activation function.

$$Y = \sigma(W * X + b) \tag{1}$$

$$Y = \sigma(W \cdot X + b) \tag{2}$$

ii) DenseNet

The Densely Connected Convolutional Network (DenseNet) architecture was developed for deep learning to solve the vanishing gradient problem and promote the reuse of features in deep neural networks. DenseNet allows for an increase in the flow of information throughout the network [26], where every layer can access the gradients in its own unique way. Because of this, the loss function and access to the input layer are always available, enabling deeper training. When building a DenseNet model, each successive layer inputs the feature maps of all the layers that came before it [27]. DenseNet is an effective solution to the problem of vanishing gradients and has a significantly reduced number of parameters. Equation (3) represents the Dense Block, and Equation (4) represents the H Function where Y is the output, $X_0, X_1, \ldots, X_{n-1}$ are the input feature maps, W_1 *and* W_2 are weight matrices, b_1 *and* b_2 are bias vectors.* denotes the convolution operation, σ is the ReLU activation function.

$$Y = H([X0, X1, \ldots, Xn - 1]) \tag{3}$$

$$H(\cdot) = \sigma(W2 * \sigma(W1 * \cdot + b1) + b2) \tag{4}$$

iii) ResNet-50

Kaiming developed ResNet-50 for residual learning, which utilizes shortcut acquaintances for each of the 33 filters, thereby directly attaching the input of the kth layer to the (k + x)th layer [28]. As the depth of the network increases, the spatial dimensions gradually become less significant. The classification process is finished by applying global average pooling and fully connected layers. Because of its capacity to handle deeper architectures and ease the vanishing gradient problem, ResNet-50 has been widely employed and has achieved outstanding performance in a variety of computer vision applications. Equation (5) represents the Architecture and equation (6) represents the Residual Block Where $F(x)$ is the overall mapping to be learned. $H(x)$ is the residual mapping, x is the input to the block, W_1 *and* W_2 are weight parameters, σ denotes the ReLU activation function.

$$F(x) = H(x) + x \tag{5}$$

$$H(x) = W_2 \sigma(W_1 . x) \tag{6}$$

iv) InceptionV3

InceptionV3 is one of the more popular CNN designs, which stacks eleven Inception models. Each model contains pooling layers and convolutional filters [29] with rectified linear units serving as the activation function. In the proposed approach, a 2-D image is used as the input that contains sixteen sections of the brain that are flat and arranged on a 4-3-4 gridiron formed by the preprocessing step. Additionally, InceptionV3 implements a number of different approaches, such as batch normalization, factorized convolutions, and auxiliary classifiers, all of which contribute to its enhanced performance [30]. The model has proven to be very effective in a variety of computer vision tasks, including picture classification, object recognition, and image segmentation, and has been widely adopted in the community of computer vision researchers. Equation (7) represents the Inception Module Where Y is the output, X is the input, W_1, W_2, W_3, W_4 are weight matrices for different convolutions, $\oplus$ denotes concatenation.

$$Y = \sigma(W1 * X) \oplus \sigma(W2 * X) \oplus \sigma(W3 * X) \oplus \sigma(W4 * X) \tag{7}$$

3.3. Explainable artificial intelligence

A model of artificial intelligence, its anticipated influence, and any potential biases are all described using explainable AI [31]. It assists in defining the accuracy of models, fairness, transparency, and outcomes in decision-making that is powered by artificial intelligence. Many people have the misconception that machine learning models are incomprehensible and cannot be interpreted. Deep learning uses neural networks, among the most challenging computational models for a human to comprehend. One such technique is Layer-wise Relevance Propagation (LRP) [32], which assigns relevance scores to the characteristics input into the model. This method assists in comprehending the contribution that each feature makes to the model's prediction.

3.4. oneAPI and optimization

Herein, we considered oneAPI to enhance our suggested architecture as well as the optimizations made available by the oneDNN library. The oneAPI framework enhances processing performance by efficiently harnessing the parallel computing capabilities of multi-core CPUs and graphics processing units (GPUs). Additionally, it offers the capability to effectively utilize hardware resources through a unified source code, simplifying the execution of applications on diverse hardware platforms and enhancing their mobility. This enables developers to enhance the performance of their apps across a broader spectrum of hardware configurations. As a result, our deep learning models can be smoothly implemented on various processors because oneAPI has a unified programming paradigm, which we leverage [33]. This allows us to make the most of the computing capabilities of the currently available hardware. The execution performance and runtime of our architecture were improved as a result of the optimizations offered by oneDNN, which include parallelization and memory optimization. Because of these enhancements, the deep learning models used in the proposed architecture can perform calculations faster, experience less overhead when accessing memory, and achieve improved overall performance [34]. As a direct consequence, training and inference times are reduced, making the implementation of our suggested architecture for real-world applications more effective and scalable.

4. Results and discussion

The results obtained from the various models were tested across multiple metrics with a standard experimental setup, which is discussed in the following section.

4.1. Experimental setup

In this work, we employed Intel's Developer Cloud and the oneAPI toolset to test the deep learning models. OneAPI is a free-of-cost toolkit provided by Intel. It is a cloud-based platform. In order to improve the models' overall functionality, an optimization process was carried out using oneDNN. The studies were run via a Central Processing Unit (CPU) without a Graphics Processing Unit (GPU). The LGG Segmentation Dataset, which is a publicly available dataset collected from the TCGA LGG collection, was used for the evaluations.

Table 3
OneAPI Benchmark Results.

S: No	Models	Runtime (minutes)	Energy Utilization (Joules)	Memory Utilization (GB)
1	ResNet-50	3.2	929	2.7
2	VGG16	4.1	1200	3.5
3	InceptionV3	4.7	1669	4.0
4	DenseNet	5.6	2240	4.8

4.2. Results and analysis

The performance of the suggested architecture for classifying brain tumours was compared to that of traditional models, such as ResNet-50, VGG16, InceptionV3, and DenseNet, based on accuracy, precision, recall, and F1-score. The training and validation sets were used as part of the training process. Additionally, to ensure robustness, a five-fold cross-validation approach was adopted. The dataset was divided into folds, with around 70 % of the data allocated for training purposes and the remaining 30 % reserved for validation. The training subset comprised 2750 images, whereas the validation subset encompassed 1179 images. These subsets accounted for 70 % and 30 % of the entire dataset. The aforementioned subsets were employed iteratively throughout the five folds. Table 2 provides the validation accuracy, precision, recall and F1-Score with mean ± standard deviation values. Furthermore, to assess our models' computational efficiency, we measured runtime, energy use, and memory utilization, with a specific emphasis on oneAPI benchmarks. Table 3 presents a concise overview of the primary performance measures associated with each model. These measurements offer a comprehensive viewpoint on the performance and effectiveness of each model, with a particular emphasis on oneAPI benchmarks. The findings provide significant contributions that extend beyond conventional accuracy metrics, thereby presenting a more holistic evaluation of the models' performance inside the oneAPI framework.

The proposed architecture captured more comprehensive and discriminative features due to the implementation of image fusion and multiple CNN models, which ultimately led to improved classification performance. It is worth mentioning that ResNet-50 had exceptional performance in all evaluation measures, hence demonstrating its efficacy in accurately categorizing medical images. In addition to evaluating classification metrics, our analysis extended to examining the computational efficiency of our models by utilizing oneAPI benchmarks. The benchmarks include measures of runtime, energy utilization, and memory utilization. Upon analyzing the efficiency metrics, it is evident that ResNet-50 not only exhibited superior performance in terms of classification accuracy but also had the highest level of computing economy among the models considered. ResNet-50 exhibits a notable equilibrium between accuracy and computational efficiency, as evidenced by its superior performance in terms of runtime, energy use, and memory needs compared to other models under consideration. Based on the findings obtained, it is evident that ResNet-50 emerges as the most favorable model for the purpose of medical image classification within the scope of our investigation. With its strong categorization metrics and effective resource allocation, this technology emerges as a leading candidate for implementation in real-world healthcare environments. This study highlights the significance of taking into account both the classification performance and computational efficiency when choosing a model for the analysis of medical images. It emphasizes the realistic compromises between accuracy and resource demands. This suggests that the proposed architecture will deliver a more reliable classification of brain tumours by using the ResNet-50 model. Sample predictions can be seen in Fig. 2.

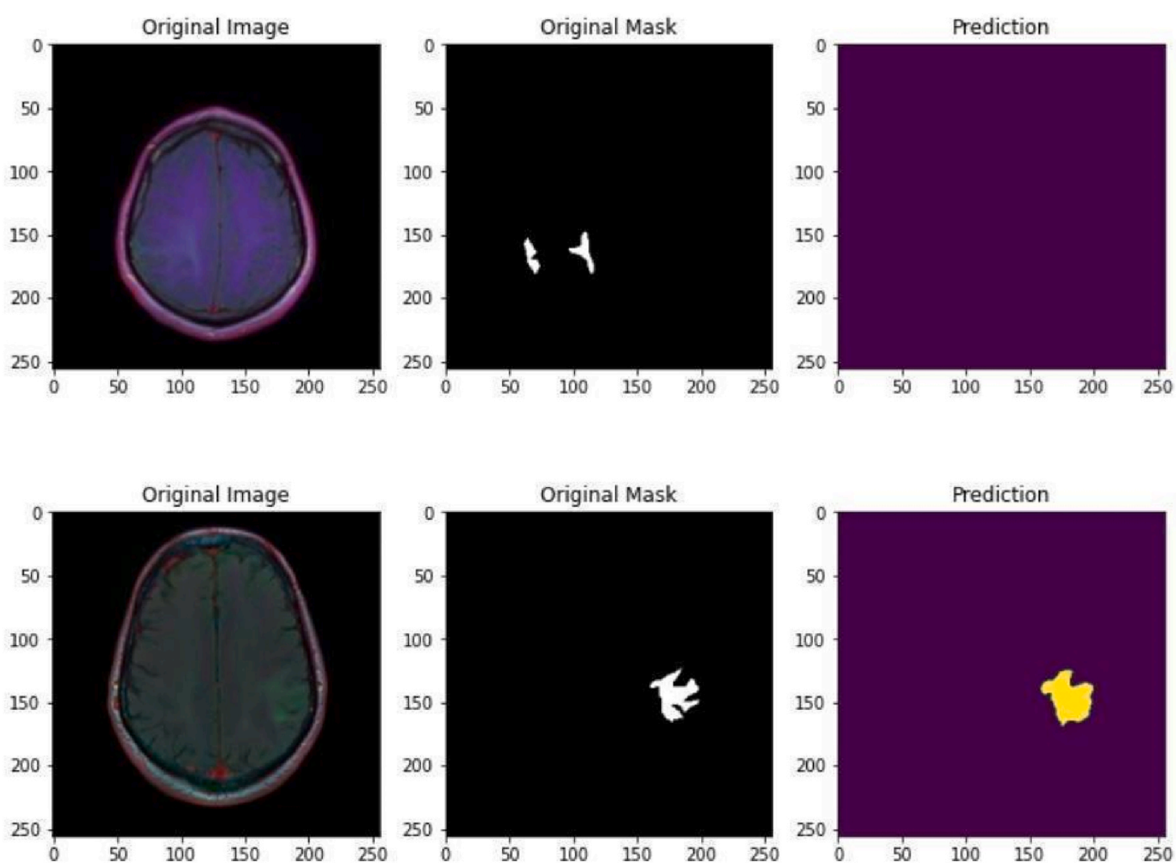

Fig. 2. Sample prediction.

5. Conclusion and future work

This work developed a novel CNN architecture based on InceptionV3, ResNet-50, VGG16, and DenseNet for the classification of brain tumours. The efficiency of the proposed architecture was compared to those of more conventional models. The findings made it abundantly evident that the proposed design largely outperformed the conventional models with regard to accuracy, precision, recall, and F1-score. Adding mIoU to our examination framework reinforces our commitment to a thorough and intuitive CNN architecture evaluation. Our study contributes to strong evaluation criteria to improve medical image classification model reliability and interpretability as the medical imaging community evolves. Specifically, the accuracy of the suggested architecture was measured at 96.2 %, which is higher than that of ResNet-50 (95.5 %), VGG16 (91.04 %), InceptionV3 (71.54 %), and DenseNet (94.65 %). Optimizing the models with oneAPI gave a good improvement in model performance. In addition, the proposed architecture consistently outperformed the conventional models in terms of precision, recall, and F1-score. The suggested architecture successfully merged the MRI images with the segmented tumour regions, which enabled the preservation of anatomical details as well as information regarding the location of the tumour. The usage of several CNN models facilitated an improvement in feature extraction, subsequently resulting in the accurate classification of tumours via the capture of a greater breadth and depth of data. These findings highlight the usefulness and superiority of the suggested architecture for brain tumour categorization. Implementing Layer-wise Relevance Propagation (LRP) provided valuable insights into the model's decision-making process. Combining all four models and LRP offers a promising identification and interpretation strategy for brain tumours. In spite of this, we acknowledge that clinical validation is still an essential step in the course of this development. As a component of our ongoing research agenda, we want to carry out a comprehensive clinical validation procedure to evaluate the model's effectiveness in actual healthcare environments. Patients suffering from brain tumours may benefit from increased diagnostic accuracy provided by the suggested design and assistance with treatment planning. In the future, the proposed architecture can be refined to investigate various fusion methodologies or incorporate more medical imaging modalities to improve classification performance. This research, in its entirety, contributes to the rapidly expanding field of medical image processing and indicates the potentially fruitful application of CNN architectures in categorizing brain tumours. In the field of neuro-oncology, the proposed architecture provides a reliable and accurate solution for medical professionals, enabling them to make better decisions and eventually results in better patient outcomes.

CRediT authorship contribution statement

Akshay Bhuvaneswari Ramakrishnan: Visualization. **M. Sridevi:** Methodology. **Shriram K. Vasudevan:** Supervision. **R. Manikandan:** Validation. **Amir H. Gandomi:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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