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Efficient brain cancer identification using ResNet50 and ResNet50 V2: a comparative study with a primary MRI dataset

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ABSTRACT

Primary malignant brain tumors along with central nervous system cause a significant amount of deaths every year, making brain cancer a major worldwide health problem. In South Asian countries, the number of patients suffering from brain cancer is steadily rising. Treatment effectiveness and improved patient outcomes depend on early detection. Using a dataset consisting of 6056 original raw MRI scans, this study evaluates how well convolutional neural networks (CNNs) diagnose brain cancer. We present ResNet50 and ResNet50V2 models assessed for their effectiveness in identifying brain cancers. Transfer learning and fine-tuning were employed to enhance model performance. The models demonstrated strong performance, with 87-99% accuracy rate. ResNet50V2 achieved the highest 99% accuracy. To detect tumor early, this work emphasizes how well the CNN-based machine learning methods help as timely intercession and patient care is necessary. Early prediction with 100% confidence and reliable precision is a critical issue in the modern world. Our goal is to use advanced algorithms to forecast images affected by cancer. Lastly, we will deploy an automated system that will enable us to confidently identify images affected by cancer. Our suggested methodology and its application could significantly impact the field of medical science by combining computer vision and health informatics.

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1. INTRODUCTION

The human brain, which is an essential organ, is responsible for the entire process of control and decision-making. This section needs to be kept safe from injury and disease since it is the controlling center of the nervous system [1]. Every part's final stage is the reason for mortality in cases of different types of brain cancer or tumors. Hence, focusing on prevention or treatment is crucial, particularly in the brain organ. One of the conditions that can immediately endanger people's lives is brain tumors. By 2023, the American Cancer Society predicts that 25,400 cases of cancerous brain or spinal cord tumors will be found. Of these cases, 14,420 will be in men and 10,980 will be in women. These figures would be substantially higher if benign tumors (tumors other than cancer) were included. Nearly 18,760 persons (10,690 men and 8,070 women) lost their lives to malignancies of the brain and spinal cord every year [2]. We gather a healthy dataset on brain tumors, which include meningitis, glioma, and other tumors classified as brain cancer. The dataset was assembled by our team with assistance from several Bangladeshi hospitals [3]. The primary motivation for implementing a real-time responsive prediction system and an advanced deep learning technique with excellent accuracy is the large number of fatalities and serious injuries. This will allow those directly impacted by brain cancer or tumors to be detected early and avoid requiring significant surgery. This classification depends entirely on images, which are divided into three categories. To make our study more effective and profitable, we analyzed and researched earlier studies. The review of the literature is shown below.

Deshpande and others implement the neutrophilic set, entropy-based methods, deep neural networks, and other methods that are now used to categorize brain cancers. A convolutional neural network (CNN) architecture correctly identified 96.56% of meningiomas, gliomas, and pituitary tumors. A CNN-based CAD system for brain tumors had a 94.74% classification accuracy. Brain tumors were detected with 98% accuracy using ResNet50 in MRI images [4]. To identify brain tumor with MRI image-based dataset, Islam *et al*. [5] implemented a federated learning (FL) method. The base ensemble framework outperformed with an accuracy of 96.68%, whereas the accuracy achieved by the FL approach was 91.05%. The paper states that DenseNet121, InceptionV3, and VGG19 are the three CNN models performing best in an ensemble setting. Disci *et al.* [6] have studied CNN and CAD-based disease diagnosis. Transfer learning models and customized characteristics are used in brain tumor detection. Brain cancers are identified using deep learning techniques and fusion processes, whereas normal brain tissues are identified using Bi-LSTM. Chattopadhyay and Maitra [7] suggested model for brain tumor identification which gained an exceptional accuracy of 98.74%; by outperforming earlier state of art findings. After training different datasets consisting of MRI scans with different tumor features, a CNN and then conventional classifiers has been used to train the model. It used RMSProp as the final layer's optimizer and softmax activation function. Abd-Ellah *et al*. [8] identified MRI abnormalities using the hybrid abnormality detection algorithm (HADA). PNN, segmentation, feature extraction, and preprocessing extraction are employed to identify brain tumors. DNN for automatic CNN based brain tumor localization, averaging 0.88 on the DICE score. Chandni *et al*. [9] proposed a novel CNN-based MRI diagnostic method for classifying brain tumors. Validation accuracy is 98.70% without any data augmentation. In case of the CE-MRI dataset, this system outperforms current techniques.

Yaqub *et al.* [10] compare eight CNN optimizers that make use of gradient descent. The Adam optimizer yields the highest classification and segmentation accuracy of 99.2%. To categorize brain tumors, Montaha *et al.* [11] recommended a hybrid model called time distributed CNN LSTM (TD-CNN-LSTM). Effectively merging LSTM with 3D CNN, the model outperforms 3D CNN and obtains a test accuracy 98.90. For the purpose of segmenting brain tumors, Chen *et al.* [12] proposed the CNN-Transformer parallel network CSU-Net. It focuses on the shortcomings of CNN and Transformer's information processing. Highlights the recent attention that CNN and Transformer have received for segmenting brain tumors. Alturki *et al.* [13] describe a hybrid model that uses CNN characteristics to identify brain tumors. They achieved 99% accuracy in identifying brain cancers. Rehman *et al*. [14] propose deep learning and a 3D CNN to detect and categorize microscopic brain cancers. 98.32%, 96.97%, and 92.67% accuracy are obtained from the BraTS datasets. The outcomes' advantages and disadvantages are carefully examined by Kumar *et al*. [15]. Prototype results are used to extensively analyze and test a variety of current brain neoplasm detection approaches, including deep neural networks and data mining algorithms like Apriori and k-means clustering, which show potential classification accuracies of up to CNNs obtained 98.67%.

Liu *et al.* [16] applied various transfer learning models for instance, AlexNet, Vgg16, ResNet18, ResNet50, and GoogLeNet. The improved f-measure, recall, and accuracy of the AlexNet model were demonstrated. Techniques for augmenting data were applied to improve generalization and reduce overfitting. Traditional approaches and sophisticated deep learning algorithms, such as CNN, have been investigated for MRI classification. After only 10 epochs, Roy *et al*. [17] achieved 90% accuracy, and after 50 epochs, they achieved 97% accuracy. Furthermore, prior work emphasizes the use of deep learning and transfer learning approaches to enhance brain neoplasm classification through the use of algorithms with image pre-processingation techniques. Senan *et al*. [18] highlight the significance of early brain tumor diagnosis. Notable developments include hybrid models (ResNet-18 and AlexNet) that fuse deep learning and machine learning (SVM). Demonstrating outstanding results. As an illustration, the hybrid AlexNet+SVM method has very good results, displaying 95.50% specificity, 95.25% sensitivity, and 95.10% accuracy. Badža and Barjaktarović [19] mates used a novel CNN architecture to obtain a 96.56% classification accuracy for brain cancers. The network is tested using T1-weighted contrast-enhanced MRI images, along with that, its performance is evaluated using 10-fold cross-validation. The study aims to improve real-time detection and generalization ability during brain surgery, presenting the developed CNN architecture. Younis *et al*. [20] explore VGG-16 ensembling for brain tumor analysis using deep learning with impressive accuracy (98.14%). This study uses the CNN model architecture with transfer learning and deep learning models. With precision scores of 99.4% for gliomas, 96.7% for meningiomas, and 100% for pituitary tumors, the total accuracy of 99% is rather remarkable achieved by Reza *et al*. [21]. With accuracy ranging from 73% to 99%, several methods, including SVM, neural networks, and probabilistic neural networks, have been used to identify brain tumors.

Tehsin *et al*. [22] present the disease and spatial attention model (DaSAM), a unique model. They achieved 86% accuracy in brain tumor diagnosis by using this on two multiclass datasets. By using the AlexNet-CNN architecture model on MRI data, Badiji and Ülker [23] were able to classify brain cancers with a very high accuracy of 99.62%. With a total of 2000 datasets and a 99% accuracy rate, VGG16 and VGG19 has been used to categorize brain MRIs into two classes by Rajinikanth *et al.* [24]. Karaddi and Sharma [25] present novel approaches to brain tumor segmentation and classification in MRI images using explainable artificial intelligence (XAI). With DeepLab V3 tuned, they earned an average segmentation accuracy of 92.68% with a somewhat high classification accuracy of 95.42%.

A comparative visual and analytical summary of earlier existing studies is shown in Table 1. That will assist us in closing the gap and provide us with concept information gleaned from the literature study analysis.

Table 1. Comparative analysis of existing works

SL. no	Author information	Studies	Dataset details	Achievements
01	Deshpande *et al*. [4]	ResNet50 and others CNN Models	Image data and focus in raw scanned image	98% accuracy on brain cancer dataset
02	Islam *et al*. [5]	FL and ensemble techniques	MRI image-based brain tumor identification	96.68% accuracy achieved
03	Chattopadhya and Maitra [7]	CNN based algorithm	MRI images used to make this research	98.24% accuracy to predict only brain-tumor
04	Montaha *et al*. [11]	Distributed-CNN-LSTM (TD-CNN- LSTM)	3D dataset are used in this case study	98.90% accuracy identify brain cancer using 3D CNN
05	Kumar *et al*. [15]	CNN and SVM classifiers	3064 MRI images of brain tumors	96.13% accuracy
06	Roy *et al*. [17]	Deep learning techniques	Image based dataset with two class	97% accuracy
07	Senan *et al*. [18]	Developed hybrid models (ResNet-18 and AlexNet)	Image data	Highest accuracy 95.5%.
08	Badža and Barjaktarović [19]	CNN	Image data	96.56% classification accuracy in MRI images
09	Younis *et al*. [20]	VGG-16	Binary class image data	98.14% accuracy
10	Reza *et al*. [21]	SVM, neural networks, and probabilistic neural networks	Three class of image dataset	73-99% accuracy
11	Tehsin *et al*. [22]	Customized CNN-DaSAM	Two multiclass dataset	86% accuracy
12	Badiji and Ülker [23]	AlexNet	MRI image dataset	99.62% accuracy
13	Rajinikanth *et al.* [24]	VGG16 & 19	Teo class MRI images	99% accuracy
14	Karaddi and Sharma [25]	DeepLab V3	Fig share dataset	Segmentation accuracy 92.68%, classification accuracy 95.42%

We immediately examine more than 20 prior articles to assess their research and identify any knowledge gaps. Studies on real-time detection are scarce; in particular, there are few restrictions on using the technology for direct consumer applications. Furthermore, we discovered that the majority of the datasets are of low quality, and some of them are not operational. Some MRI scans are obsolete for current technology, and a predictive system is not available as an application. Based on a review of other studies that identified shortcomings in their dataset and findings because of things like model implementations and data quality. Completing any gaps in this work is a significant contribution by observation.

- We have compiled a healthy and dependable MRI dataset, which improves the caliber of the study.
- We employ advance deep learning model that performs better than baseline models.
- We demonstrated our highest level of accuracy and confidence with others measurement matrix.
- Lastly, we create a real-time cancer prediction web application using photos.

2. METHOD

We used a passive research procedure in this study, provided an impactful approach, and focused on our methodology to put it into practice. A methodical process is followed from data collection to cancer prediction (Figure 1). We first build the dataset before running the entire model. We are using various machine learning classification models in our research on brain cancer categorization. However, gathering datasets is one of the most challenging tasks. Initially, we decided to use the dataset we had gathered independently. When we were able to obtain MRI images from multiple hospitals and have them confirmed by a board-certified medical doctor. After pre-processing the data using several variables, we put the model into practice. The proposed method, which outlines our entire procedure, is shown in Figure 1. There are multiple sections to finish the entire procedure. We go over each step of the procedure in different subsections (2.1 to 2.3).

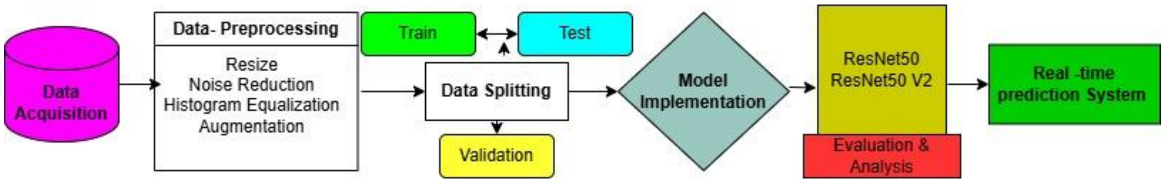
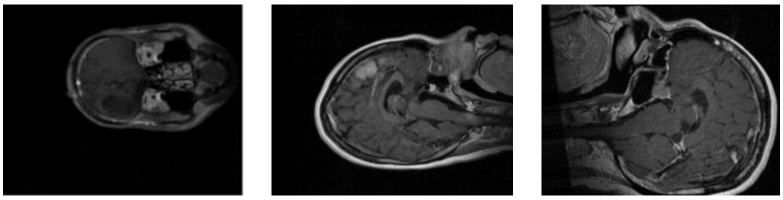


Figure 1. Proposed methodological flowchart

We use the prediction method as an ML kit and integrate this into a web application for real-time prediction after receiving a satisfactory result from the deployed model. Segment 4 briefly discusses this.

2.1. Dataset description

Initially, we attempted to obtain raw data from some reputable hospitals in Bangladesh for data collection. We receive our raw data from Bangabandhu Sheik Mujib Medical University (BSMMU), IBN SINA Medical College, and LAB-AID Hospital. The Daffodil International University Research Ethics Committee has validated this procedure as ethical. Furthermore, Dr. Hameem Ashraf, a domain expert (Medical Consultant, Medi lab Diagnostic Center, Dhaka), has verified this data. We collect-Meningioma, glioma, and brain tumor are the three classes that make up the dataset. Three groups (meningioma, glioma, and brain tumor) provided 6056 JPG MRIs. It contains data from 2048 on tumors, 2004 data on meningiomas, and 2004 data on gliomas [3]. In Figure 2 represents the sample data: Figure 2(a) denotes glioma, Figure 2(b) menin, and Figure 2(c) represents the sample of tumor of brain.



(a) (b) (c)

Figure 2. Sample dataset of each class; (a) glioma, (b) menin, and (c) tumor

2.2. Data pre-processing

To improve the data quality and ensure that it is suitable for the model's implementation, we employed various pre-processing techniques (A-E). Histogram equalization is one of the most important advanced techniques to purify data, providing clear and excellent color contrast. Resize is used for the ideal model fitting, and noise reduction is used to improve the data quality. Splitting and augmentation are also used to accomplish the ultimate achievements. Each of them is described below.

a. Resize: firstly, we take our raw data into 512×512 pixels for implement algorithms.
b. Noise reduction: we apply gaussian filters for remove noise from the image without loosing important facts. It functions as both cumulative gaussian filters and isotropic filters, and it can blur images. It acts as low-pass filters.
c. Histogram equalization: image optimization is achieved by a procedure called histogram equalization. The contrast and brightness of each image are different in this case. To get the same contrast and brightness, we thus use the histogram equalization technique.
d. Augmentation: our training data objectives were met with the aid of data augmentation. To enhance color and positioning, the following techniques were used: increase brightness, decrease brightness, horizontal flip, vertical flip, rotate 180, rotate 90 counter-clockwise, rotate 90 ClockWise, random rotation (90, 180, or 270 degrees), random brightness adjustment, distortion, bending, scaling, and noise addition were all included in the data augmentation process. This procedure increases the quantity of data that is fitted into the model, guards against overfitting, reduces bias in the model, and improves model performance,

particularly on ResNet50V2. Table 2 represents the raw images number and number of augmented images by using multiple augmentation process which is already describe, we can find that we make a huge change after finalize augmented data the total amount of data is 48448.

Table 2. Class wise-dataset augmentation

Plant species	Class name	Total images	Augmented images
Brain cancer	Brain glioma	2004	16032
	Brain menin	2004	16032
	Brain tumor	2048	16384
	Total	6056	48448

e. Splitting: in order to evaluate models accurately, the dataset has been splitted into three parts: training (80%), validation (10%), and testing (10%). The model is trained using the training data set, hyperparameters has been adjusted. Overfitting is minimized using the validation set, and the model's final performance is assessed using the test set.

2.3. Model implementation

We utilize many deep learning models and apply each one in the most effective manner possible. This study reports on the performance and unique visualizations of ResNet50 and ResNet50V2. By comparing and analyzing earlier studies, we are able to determine that while the generic CNN Model is implemented, there are other models that can perform better, which is why we have selected these two specific models.

a. ResNet50: ResNet-50 is a CNN design that is part of the residual networks (ResNet) family. ResNet is a group of models that were made to make deep neural network training easier. The Microsoft Research Asia experts created ResNet-50, a deep learning model that is famous for how well it does at categorizing pictures into groups [26].
b. ResNet50V2: a residual network, or ResNet amplification, is a kind of neural system that Microsoft established in 2015 while it won the ImageNet content. The ResNet network configuration is utilized by the network ResNet50. The engine that drives the new reminder mapping technology is ResNet which deals with the dirt problem. It has larger than 23 million trainable parameters in its 50 layers. It uses extensive regular combining rather than layers that are finally connected, in contrast to other conventional DCNN systems [26]. The structure of this model is shown visually in Figure 3, where it is evident that various layers are used to segment images at different layers. Max polling, fully connected layers, and convolutional (C) layers all contribute significantly to the final result. The C-layer segmentation of our dataset is initiated by the max pooling layer. The image appeared refined and fluid on average layer. Using picture segmentation, the final fully connected layer with dropout layer reaches the maximum prediction.

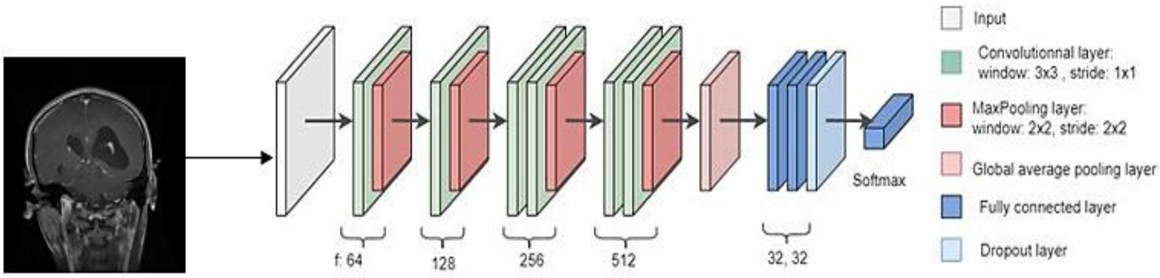


Figure 3. Architectural visualization, action, and components of ResNet50V2

3. RESULTS AND DISCUSSION

This raw core dataset, we were achieved to highly satisfactory accuracy result. It is quite well reflected in several outcome discussion dimensions. The different matrix and analytical results presented here, each with its own section, provide the proof of our achieved outcome.

3.1. Performance measurement metrics

Important parameters including F1-score, recall, precision, and accuracy were taken into account during our study. These certain metrics enable a comprehensive evaluation of the models' ability to identify brain cancer and provide insightful information for useful medical science applications.

- Accuracy: accuracy=$\frac{TP + TN}{TP + TN + FP + FN}$ (1)

- Precision: precision=$\frac{TP}{TP + FP}$ (2)

- Recall: recall=$\frac{TP}{TP + FN}$ (3)

- The F1-score: F1-score=$\frac{2 * Precision * Recall}{Precision + Recall}$ (4)

Here, TP, TN, FP, and FN are in full form, respectively: true positive, true negative, false positive, and false negative [27], [28]. Additionally, we calculate the AUC value to improve comprehension.

3.2. Result discussion of preprocessed dataset

The two original CNN networks—ResNet50 and ResNet50v2—are contrasted in this section. Performance in classification comes first. The overall metrics of both models are then examined. We present ResNet50v2 and ResNet50 and provide information on how accurate each architecture is at detecting brain cancer. Notably, the results demonstrate that the models with the highest accuracy of 99% were ResNet50v2. On the other hand, ResNet50 achieved an accuracy of 87.8%. It showed a marginally decreased performance compared to its counterparts. We see that in every matrix, it presents a 99% accurate result. Divided the dataset into 80% train, 10% test, and 10% validation checks during the model's implementation with 256 batch size in 30-50 epochs. In Table 3 class wise factor result are given that can present the summary of every class.

Table 3. Class wise result summary of two models

Model name	Class name	Precision	Recall	F1-score	Support
ResNet50	Glioma	0.92	0.96	0.94	401
	Meningioma	0.94	0.86	0.89	401
	Tumor	0.93	0.97	0.95	410
ResNet50V2	Glioma	1.00	1.00	1.00	2004
	Meningioma	0.99	0.99	0.99	2004
	Tumor	0.99	0.99	0.99	2048

Table 4 summarizes two implemented models. It is essentially a weighted average result for both models. ResNet 50 achieved 71-88%, with an AUC value of 50%. And because of every factor is 99% and the AUC value is 68%, the ResNet50V2 models are really satisfied.

Table 4. Final weighted average result summary

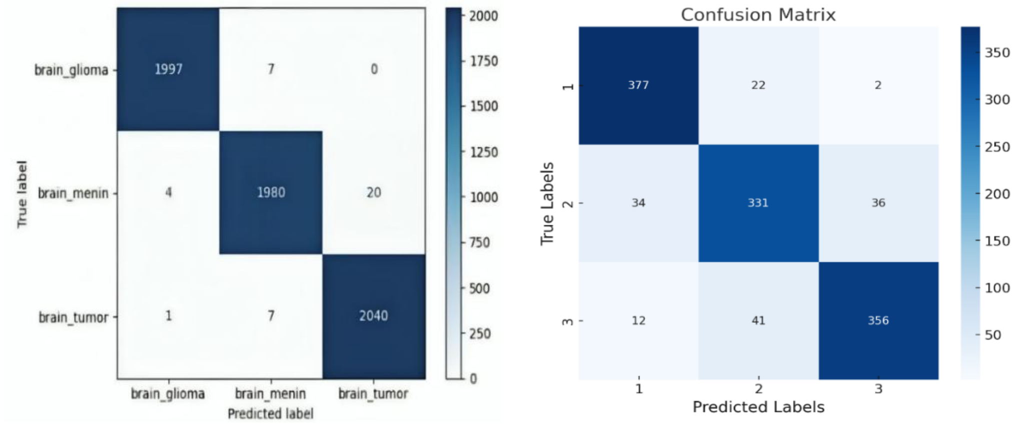
Models	Accuracy (%)	Precision	Recall	F1-score	AUC
ResNet50V2	99	0.99	0.99	0.99	0.68
ResNet50	87.8	0.76	0.71	0.73	0.50

3.3. Confusion matrix

The result's evidence and actuality are presented in the confusion matrix. Figure 4 shows the confusion matrix for our two models. The confusion matrix for ResNet50 is displayed in Figure 4(a). It demonstrates that there are discernible false positive and false negative values in addition to the fulfilled True Positive value. The second class's false positive and false negative values are relatively high, and there are minor categorization issues with the other two classes. On the other hand, Figure 4(b) displays the best accuracy result, with the other factors—FP, FN, and TN—also showing high levels of satisfaction and the True positive value being delighted. The CF matrix in ResNet50 models exhibits limitations, such as miss classification and FP and FN rates. However, ResNet50 V2 can achieve a high positive rate while reducing miss categorization. Based on the confusion matrix analysis, our models' performance satisfaction level is pretty good and consistent.

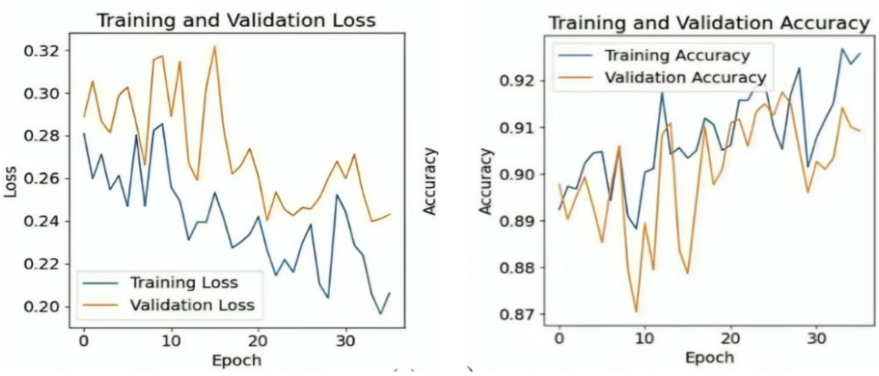
3.4. Accuracy and loss graph

We present the accuracy and loss graphs from the perspectives of the train and test cases to help better understand the quality and authenticity of the result. The resNet50 models' training and test loss lines are shown in Figure 5(a), with a value in the range of 0.1–0.3, indicating that both of our models' performances are reasonably good and that is noticed on Figure 5(b). There is some noise on the accuracy graph, but it is still in good condition. The best result is displayed in Figure 6, there is presented that 92–99% accuracy and it is cleared on Figure 6(a). In loss graph Figure 6(b) there are no problems with over-fitting or under-fitting, and the accuracy line between the train and test difference values is only between 0.3 and 0.7.



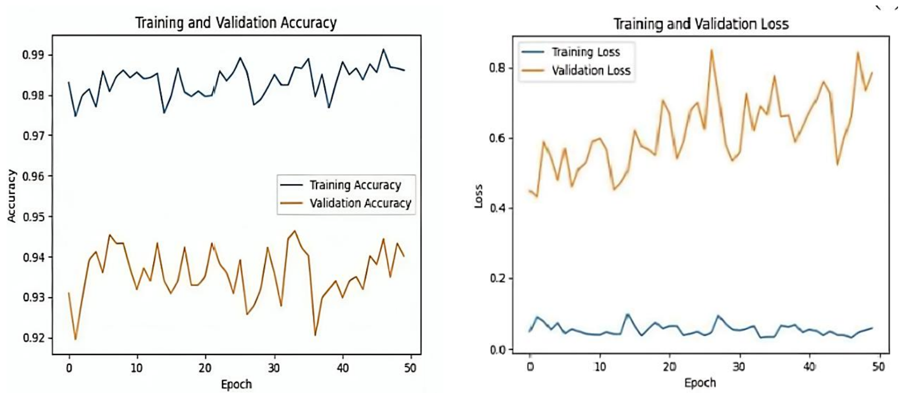
(a) (b)

Figure 4. Confusion matrix; (a) ResNet50 and (b) ResNet 50 V2



(a) (b)

Figure 5. Performance of ResNet50; (a) accuracy graph and (b) loss graph



(a) (b)

Figure 6. Performance of ResNet50 V2; (a) accuracy graph and (b) loss graph

3.5. Comparison to others implemented models

We demonstrated how we used two unique iterations of the ResNet algorithm to get the maximum accuracy, which ResNet50V2 achieved. However, we utilized over five different algorithms on our dataset. We compare and find that, with a few minor exceptions, they too provide a steady result. Table 5 displays the results of the other models, including VGG16, Xception, and Pytorch summaries. Our dataset is comprised solely of test and train accuracy, and we can demonstrate that the ResNet50 and ResNet50v2 models provide the highest accuracy with no problems with overfitting or underfitting.

Table 5. Result summary of otters implemented models

Models	Train accuracy	Test accuracy	Remarks
VGG16	84	83	Models performance satisfied but accuracy low
Xception	86	91	Model becomes overfit
Pytorch	78	71	Less accuracy

4. WEB APPLICATION IMPLEMENT

We move toward an automated system so that customers can use the prediction system immediately once we have applied all of the models to our primary data. We created the brain cancer predictor as an online web application in response to this need.

4.1. Web applications for real-time prediction

We used flask to create a web application. To process our submitted image through the models and automatically produce a prediction result with a confidence level, we essentially integrate the implemented models kit as a.h5 file. The functioning flowchart of the suggested system, which is used to construct the applications, is shown in Figure 7.

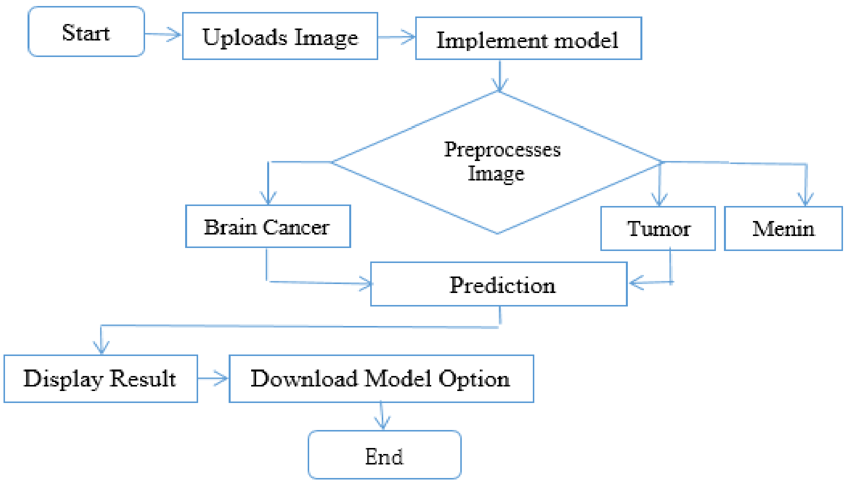


Figure 7. Working flow-chart of implemented web applications

When we upload a picture to the system, the ResNet50V2 models—which are among our best models process it and use their confidence level to predict the image category. An additional metric for assessing reliability is the confidence level. Additionally, it solely shows whether or not uploaded photographs contain cancer.

4.2. Sample output of web applications

In order to create a web application that is easy to use and conveys a clear message regarding picture prediction, we designed a simple interface. Our goal is to forecast the class and guarantee its level of confidence. Figure 8 displays an example of a web-based application's visualization, and it is clear that the tool can predict brain cancer with 100% confidence.

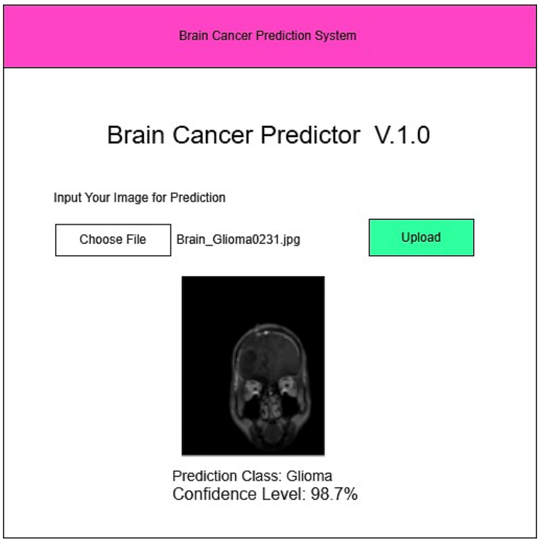


Figure 8. Visualization of brain cancer predictor web application

5. CONCLUSION

The brain is one of the most vital components of a human being. In this study, we aim to determine whether or not the brain is altered early on. Notably, our primary dataset consists of three unique tumor cases. We demonstrate the effectiveness of ResNet50 models, and in particular, we discover that ResNet50V2 models outperform other models and find their exceptional technique. After comparing various models, we eventually decided which algorithms to use. We successfully aim for 99% accuracy and 93–100% precision, recall, and F1-score in this research. Because we collected our data in an honest manner, the quality of our study is at the most significant level. Our data preparation techniques, particularly the data pre-processing and augmentations, allow the data to fit into various algorithms. By contrasting it with other models, we can demonstrate that the ResNet50 and ResNet50 V2 models are the most effective in predicting cancer images. One of our most significant contributions is developing a web application that can identify an image and provide results along with a confidence level. In this paper, we try to follow sound research practices, from data collecting to web application implementation. There are only three classes in our dataset, which means that we only consider these three categories. Future datasets may contain many classes and large volumes of data. In addition, our pre-trained model only classified the image using our pre-processing model and ResNet50V2 implementation, which produced high-quality research. However, there is still room for future work to determine which areas of the image are directly impacted by cancer, such as displaying specific object detection. One option for affected place detection is vision transfer. Additionally, we may make the web application we implemented more user-friendly and dynamic. We can claim that, if we use this strategy broadly, our research could have a significant influence on the medical sector. Particularly, if we combine several kinds of medical data into one frame, we can discover many cancers or categories on one platform. We believe that our study strategy, methods, resolution, and methodological choices will provide dynamism to the fields of medical science and health informatics, allowing us to assert that computer technology facilitates easier and more efficient processes.

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This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
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Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

ETHICAL APPROVAL

This Research is Ethically Approved by the Ethics Committee of Faculty of Science & Information Technology. The Ethical Consideration Enrollment No: DIU/FSIT/CSE/EC/24-2314.

DATA AVAILABILITY

The data that support the findings of this study are openly available in Mendeley Data at http://doi.org/10.17632/mk56jw9rns.1.

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