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Deep Learning Based Medical Image Categorization for Clear Feature Extraction

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Abstract: In the discipline of recognition, medical image recognition plays a vital role in accurate prediction and quick determination of harmful diseases. Since medical images can be employed to regulate, handle, and diagnose sickness, they are a fundamental component of a patient's medical record. Nonetheless, image categorization is a tough issue in the arena of diagnostics. This article proposes a medical image technique using deep learning to enhance image classification and grouping in the health industry. In recent years, scientific research has centered on deep learning and its utilization in medical imaging, particularly image reconstruction. Considering deep learning models outperform in a broad spectrum of vision circumstances, a great deal of work is currently being focused on reliving pictures taken medical photos. In the current era of swiftly developing technology, MRI, and CT are considered to be the most reliable imaging techniques from scientific viewpoints for detecting and categorizing different diseases. The present article provides different deep learning strategies for rebuilding photographs in addition to a detailed examination of the most prominent databases. We talk about obstacles and prospective opportunities in medical reconstruction. The outcome of the trial indicates our proposed approach functions greater and attains 98% accuracy.

Keywords: *Deep learning, Medical Imaging, Disease Detection, Accurate prediction.*

1. Introduction

Deep learning (DL) addresses have already been successfully utilized in medical picturing, which involves computer-assisted detection and diagnosed radionics, and medical image interpretation. Deep neural networks are extremely efficient, commonly with an elevated level compared to human efficiency, in an extensive variety of applications. For example, with the energy usage of popular graphic processing units, making thousands of predictions a day brings with it such a considerable amount of energy. Deep learning has been commonly used in computer vision and image processing to deal with existing pictures, boost those pictures, and produce attributes based on them. Questions over congestion and effectiveness have additionally arisen in the deep learning sector. Deep learning techniques have become more sophisticated, permitting deep models to face more complex and difficult troubles [1]. Medical imaging is an essential instrument for evaluating experimental information and determining evidence of different problems. In pathology research, magnifying medical images may offer practitioners extra details, improving diagnosis accuracy. As a consequence, the enhanced quality of medical photos becomes a hotspot. In addition, increased medical images might significantly enhance computer-aided automatic detection. In particular, an bundance of magnetic resonance imaging (MRI) and single-detector spiral CT scanners produce medical images that are beneficial to noninvasive treatment [2].

Deep learning techniques for the diagnosis of numerous diseases are being invented as an outcome of recent advances in machine learning methodologies in the field of medical image analysis. Deep learning techniques have been employed to successfully diagnose an assortment of conditions notably brain tumors, liver tumors, MRI scans, retinal vessel images, skin lesion images, and liver tumors. Due to their time-consuming character and the coarse and powdered appearance of almost all of these images, previous techniques of examination, such as made by hand methods, have been limited in their usefulness. More recently, the analysis and segmentation of medical screenshots applying deep learning formulas have produced positive outcomes. However, a scarcity of easily accessible labeled datasets for deep neural network model training significantly restricts such techniques. The present study recommends a powerful and efficient deep-learning structure for dividing medical images with an objective of sickness detection and prognosis, irrespective of lacking data for training. This work investigates the deep learning framework's usefulness employing three separate medical image varieties: retinal, external, and brain tumor images [3]. Image segmentation reveals the image's main focus, thereby aiding in medical image analysis. Methods for segmenting MRIs include determining the borders of different tumors, segmenting radiographs depending on mass, and segmenting sections of chest X-rays and CT images weakened by pneumonia. In an attempt to conquer the shortage of knowledge concerning medical picture segmentation, algorithms have been

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established. Earlier models of image segmentation incorporated edge-based, region-based, and thresholding procedures. Thresholding has been employed for splitting pixels throughout groups by their value range. Using a filter, pixels can be identified as edged or nonedged in an edge-based technique. By using region-based segmentation, comparable as well as opposite pixels were discriminated [4]. Figure 1.1, which exhibits different feature extraction layers, presents a fundamental overview of this.

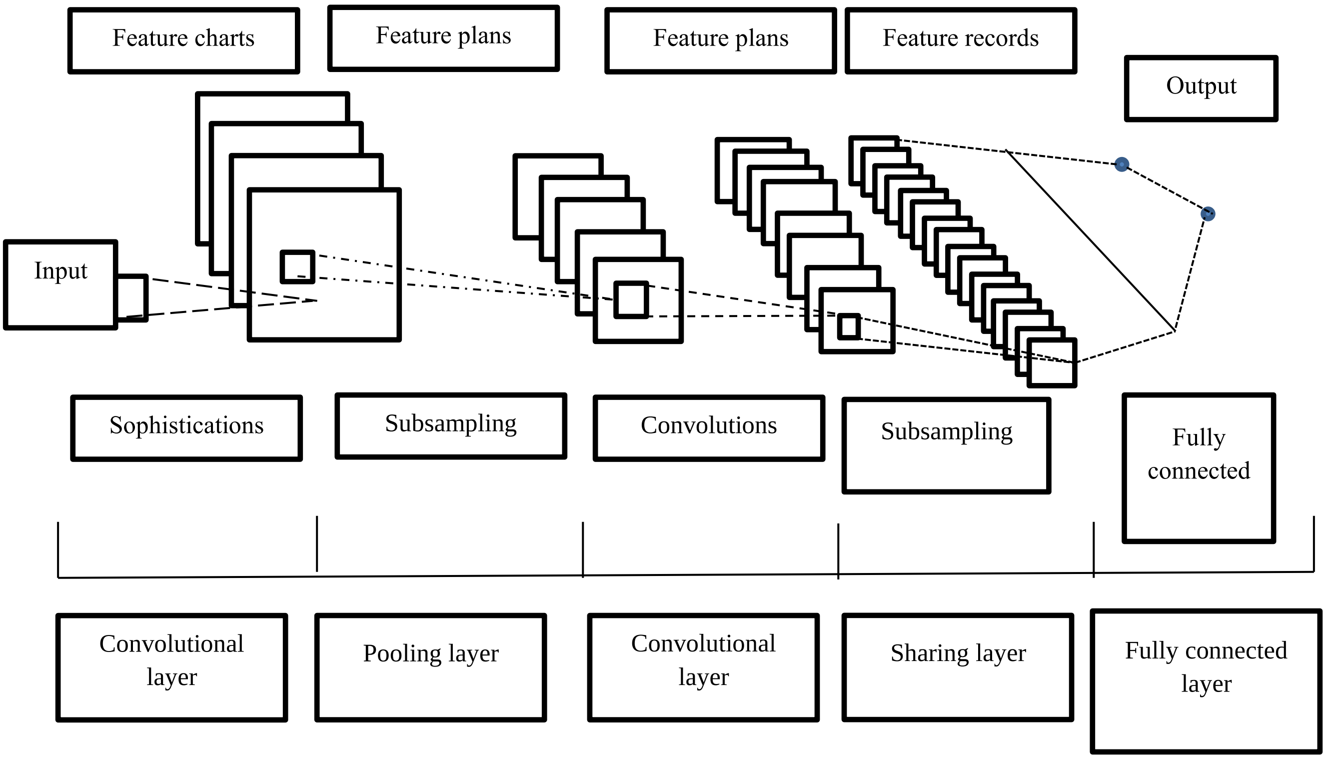


Fig. 1.1. Deep learning technique in medical imaging

Clinical employees frequently cannot combine CT images with quantitative, precise healthcare data with the naked eye; consequently, medical image evaluation and processing gadgets deal with the problem by analyzing highly intricate impact data collected from CT photographs and creating equivalent computations for further analyses. A technique that is occasionally employed in healthcare to figure out the complexity of an illness is computed tomography, or CT. It provides two benefits over X-rays: it is extremely sensitive and doesn't suffer from overlap or artifacts from X-rays. In addition, CT has the potential to deliver an improved and full portrayal of specific instances of bone lesions. Convolutional neural networks were neural systems that possess a deeper structure. It can identify feature data that is not evident to the human eye and then convert image information into visual illnesses features [5]. Deep learning provides parameters for machine learning algorithms that may incorporate raw information into intermediate feature layers. These algorithms have resulted in important improvements previously in several kinds of fields. Whereas biology and medicine are document-rich sectors, the evidence in those disciplines may become ambiguous in addition to confusing. Deep-learning techniques can be modified to tackle specific issues in different domains. We explore how deep learning may be employed for various biomedical issues which include population classification, common biological processes, and health industries, and whether specific issues are part of the biomedical system or if deep learning can enhance these tasks. The restricted amount of stipulated training data poses difficulties in other instances, as do prohibitions on acquiring protected patient information caused by privacy and legal problems. However, we consider deep learning as the catalyst powering bench and bedside breakthroughs that might influence an immense variety of biological and medical uses [6].

This piece of writing is structured as follows. In Section 2 of this article, an assessment of the literature depending on many intrusion detection companies is dealt with. Section 3 explains the Deep learning algorithm for medical image classification. The platform setup information plus the simulations conducted to assess the impact of our advised methodology are provided in Section 4. We conclude our article in Section 5.

2. Related Works

Kavitha, G. et. al [7] To differentiate between noises like movement, Gaussian, and Poisson sound, the CNN model is utilized. For learning 12,000 and assessing 1,750 photos, they used the SIPI MISC natural image information set, which was noised with one or more combinations of syllables the dataset size was 13,750 photographs. PCA filters are utilized at every single layer in the model to decrease computation time; the model has 22 layers and a 97.4% preciseness overall. Both the spatial and temporal domains are used for noise estimation. PCA is a fuzzy model developed to measure spatial domain noise in MRI images. DWT coefficients are utilized in the transformation process to estimate the domain noise. The noise volume is established considering both the spatial and transformation planes.

Huang, R. et. al [8] The latest field of research in machine learning is deep learning. It is an assortment of algorithms created through the human brain's decision-making process and data analysis. A feedforward neural network (FNN), formerly referred to as a convolutional neural network (CNN), usually consists of a fully connected layer, a pooling layer, an activation layer, an operation layer, and an input layer for data. A neural network is utilized. The standard matrix multiplication action is substituted by the convolution operation. CNN has tremendous applications in image sorting, video acknowledgment, and medical image processing. It can also determine the spatial connectivity among data fairly well. Therefore, in an attempt to support clinical imaging diagnosis, this article investigates the confirmation of nasopharyngeal cancer lesions utilizing MRI images and a deep learning algorithm.

Tajbakhsh, N. et. al [9] The author evaluated the preliminary deep learning strategies for image classification, object detection, and object segmentation, throughout other medical imaging applications. The author undertook an extensive study of the usage of generative adversarial networks (GANs) in medical images right after this landmark survey. One of the famous authors has covered both deep learning and traditional segmentation strategies in their assessment of semi-supervised, multi-instance learning, and transfer training in medical image analysis. The surveys investigated deep learning approaches that were previously offered for medical image segmentation, with an emphasis on architectural developments and training plans. The most important polls to our work studied strategies for dealing with the problems of small sample size in medical image analysis, and the researchers analyzed suggested techniques to manage label noise in genuine medical image datasets. The surveys investigated deep learning approaches that were previously offered for medical image segmentation, with an emphasis on architectural developments and training plans. The most important polls to our work studied strategies for dealing with the problems of small sample size in medical image processing, and the researchers analyzed suggested practices to handle label noise in organic medical image datasets.

Zhang, J. et. al [10] To alleviate human users of the tedious job of privately generating parameters for medical image classification, CNN models provide a unified framework for feature extraction and classification. With the goal minimize the necessity for manual annotation and develop excellent quality feature representations for the classification of histological colon cancer photos, an established researcher deployed a DCNN. For the objective of detecting lung nodules on chest CT images, the researcher created a multi-crop pooling methodology and attached it to a DCNN. Using 129,451 clinical photographs, the author trained a DCNN to detect the most widespread and dangerous skin cancerous tumors. The DCNN's performance was confirmed by 22 board-certified dermatologists. Making use of the pseudo-inverse method, a custom network layer was trained deploying the output of the last fully linked layer in a pre-trained ResNet-152 model. By combining the two distinct pre-trained DCNN architectures, the pseudo-inverse methodology provides a stronger classifier. By calculating the weighted aggregate of predicted probabilities, the scientist presented an ensemble with multiple fully-trained DCNNs and several initially trained ResNet-50 and VGGNet-16 models.

Bhattacharya, S. et. al [11] Because DL and NN can adapt to many data types across different domains, they are widely employed in a wide range of applications, including image recognition, self-driving cars, smart homes, object detection, and classification, and prediction challenges. Over the last few decades, medical science breakthroughs have significantly changed health care by making it possible for surgeons to identify and treat ailments with greater accuracy. But similar to everybody else, doctors make blunders too. A doctor's educational achievements are based on more than simply their IQ; they additionally reflect their methods of treating patients and the type of health care system that supports them. This combination enables for such an extensive range of fluctuations in clinical outcomes; consequently, machine learning is an excellent choice to boost a physician's skills in diagnosing and treating patients. One of the techniques that is often used and provides a greater degree of accuracy in forecasting and diagnosing illness is deep learning (DL). Novel advancements in the healthcare industry have been generated by the application of DL techniques.

Ghnemat, R. et. al [12] Current advances in deep learning and machine learning indicate that the performance of the neural network (NN)-based strategies for image segmentation is no longer comparable to that of classical image processing methods. As a result, an assortment of researchers has suggested updated deep learning algorithms to enhance the reliability of image segmentation in various recognition circumstances. The most widespread method for finding images is CNN, which boosts buried layer depth and consistently acquires novel identifying features to enhance segmentation accuracy. Recognizing license plates and features are two instances of successful picture recognition programs. Medical portray detection is comparatively infrequent as a result of challenges in finding medical photos and the requirement to grasp how numerous kinds of images depict various health conditions.

Hebbale, S. et. al [13] The CNN framework for brain tumor identification, "Deep Learning Approach for Brain Tumor Recognition and Splitting," had been suggested by the researcher. For the purpose to collect adequate information for deep learning, MRI pictures of the brain are initially improved. Following that, the image is pre-processed to eradicate noise and grows into appropriate for the next phase of procedure. The recommended approach distinguishes newly input images as normal or tumorous according to characteristics derived from pre-processed brain MRIs that it was taught. A fresh approach to distinguish brain malignant tumors from several kinds of MRI scans requires pre-processing photographs deploying numerous methods, namely histogram equalization, and finally using a CNN. The dataset employed in the experiment had lesions with an assortment of sizes, paperwork, qualities, and areas. A CNN had been used for the classifying task. Given the training dataset set, CNN obtained a recall of 99.66 percent, whereas, with the examination data, it reached 99.84 percent.

3. Methods and Materials

Deep neural networks and deep discovery have become an extremely helpful and popular research topic according to their outstanding work in several of benchmark problems and applications, particularly in the disciplines of control relationships, natural language processing, data retrieval, computer vision, and image analysis. The MLP, also referred to as a feedforward neural network (FNN), contains a review of the fundamental structure of deep neural networks. For the purpose of identifying the parameters ϑ to obtain an approximation of the function g, it creates a map between the input y and the ground truth z. As Figure 3.1b demonstrates, the MLP is composed of up of multiple phases, encompassing the input, concealed and output layers. Each layer can be demonstrated to contain numerous neurons, which are the basic components of deep neural networks. Neural connections spanning adjacent layers are connected, even though neurons inside the same layer are independent of adjacent ones. MLP training comprises two stages: forward propagation and backpropagation.

3.1 The Initial Stage (Propagation Forward)

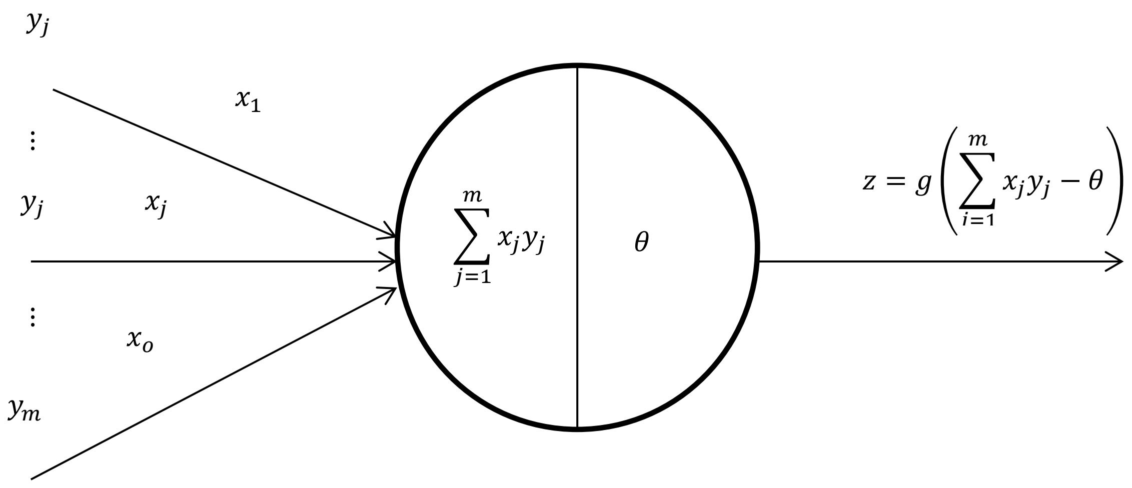


Fig. 3.1 a). The McCulloch and Pitts neuron system's composition

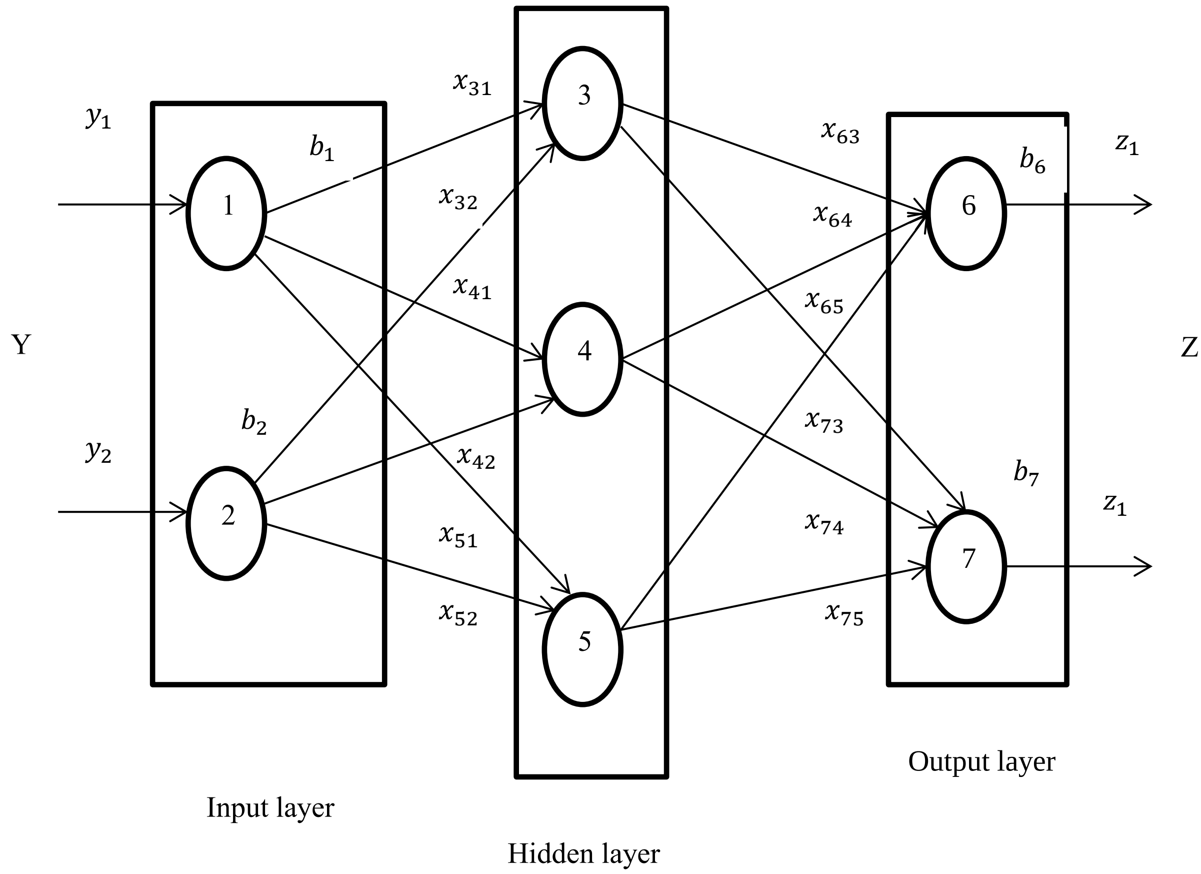


Fig. 3.1 b). Configuration of MLP

Figure 3.1 a) illustrates the M-P neural model for a single neuron. The neuron's jth input is indicated by y_j, and its corresponding weight can be seen by x_j. The upper limit is ϑ. The activation function, represented by g, regulates whether a neuron is active or inactive. Due to the M-P neural framework, if g is expressed as $(b) = \begin{cases} 0, & b < \vartheta \\ 1, & b \geq \vartheta \end{cases}$, it shows that the neuron will turn on if the sum of the weighted inputs surpasses the threshold (ϑ). If incorrect, it shall remain quiet.

As an outcome, the forward spread of MLP can be illustrated simply this:

$$a_k^{m+1} = \sum_j X_{kj}^m b_j^m + c_k^m \tag{1}$$

$$a_k^{m+1} = g\left(a_k^{m+1}\right) \tag{2}$$

The b_j^m represents the output of the j-th neuron in the m-th layer; $a_k^{m+1}$is the k-th neuron's value in the $(m+1)^{th}$ layer prior to activation; X_{kj}^m is the weight between the j-th neuron in the m-th layer and the j-th neuron in the $(m+1)^{th}$ layer; c_k^m is the bias; g is the nonlinear activation function, similar to the Sigmoid, Tanh, and ReLU.

3.2 Second stage: Backpropagation

The backpropagation algorithm is aimed at updating the MLP's weights in conjunction with the loss that is calculated by evaluating the output of the MLP against the ground truth. Proper hyper-parameter tuning (typically accomplished manually before training) can result in lower loss and a better model. The field's priority for robotic adjustments to hyperparameters is increasing. During training, loss mechanisms and optimization methods are critical as well as diverse. The loss can be determined via the following formula if the distinction between the MLP's outcome and the true situation is calculated employing squared error. M is the MLP's overall amount of layers. The output from the k-th neuron in the penultimate layer, the M-th layer, is symbolized as b_k^M .

$$F_e = \frac{1}{2}\sum_{k\in outputs}\left(z_k - b_k^M\right)^2 \tag{3}$$

The weights can be modified as shown by the following formula if the slope descent improvement function was chosen as the method called optimization. The learning rate is ρ.

$$X_{kj} \leftarrow X_{kj} - \rho\frac{\partial F_e}{\partial X_{kj}} \tag{4}$$

The modification rule for the final layer of output can be constructed as follows through the chain rule:

$$\frac{\partial F_e}{\partial X_{kj}^{M-1}} = \frac{\partial F_e}{\partial a_k^M}\cdot\frac{\partial a_k^M}{\partial X_{kj}^{M-1}}$$

$$\frac{\partial F_e}{\partial X_{kj}^{M-1}} = \frac{\partial F_e}{\partial a_k^M}\cdot b_j^{M-1}$$

$$\frac{\partial F_e}{\partial X_{kj}^{M-1}} = \frac{\partial F_e}{\partial b_k^M}\cdot\frac{\partial b_k^M}{\partial a_k^M}\cdot b_j^{M-1} \tag{5}$$

$$\frac{\partial F_e}{\partial X_{kj}^{M-1}} = -\left(z_j - b_k^M\right)b_k^M\left(1-b_k^M\right)b_k^{M-1}$$

Next, the following formula can be utilized to figure out the updated weights of the outermost layer:

$$X_{kj}^M \leftarrow X_{kj}^M - \rho\frac{\partial F_e}{\partial X_{kj}^M}$$

$$= X_{kj}^M + \rho\left(z_j - b_k^M\right)b_k^M\left(1-b_k^M\right)b_k^{M-1} \tag{6}$$

Nevertheless, the update rule is slightly different for the hidden layer:

$$\frac{\partial F_e}{\partial X_{kj}^m} = \frac{\partial F_e}{\partial a_k^{m+1}}\cdot\frac{\partial a_k^{m+1}}{\partial X_{kj}^m}$$

$$\frac{\partial F_e}{\partial X_{kj}^m} = \frac{\partial F_e}{\partial a_k^{m+1}}\cdot b_j^m \tag{7}$$

When we define,

$$\gamma_k^{m+1} = -\frac{\partial F_e}{\partial a_k^{m+1}} \tag{8}$$

Then,

$$\frac{\partial F_e}{\partial a_k^{m+1}} = \sum_l \frac{\partial F_e}{\partial a_l^{m+2}}\cdot\frac{\partial a_l^{m+2}}{\partial a_k^{m+1}}$$

$$\frac{\partial F_e}{\partial a_k^{m+1}} = \sum_l -\gamma_l^{m+2}\cdot\frac{\partial a_l^{m+2}}{\partial b_k^{m+1}}\cdot\frac{\partial b_k^{m+1}}{\partial a_l^{m+1}} \tag{9}$$

$$\frac{\partial F_e}{\partial a_k^{m+1}} = \sum_l -\gamma_l^{m+2}\cdot X_{jk}^{m+1}\cdot b_k^{m+1}\left(1-b_k^{m+1}\right)$$

As an outcome, the connection between the γ_k^{m+1} and γ_l^{m+2} can be shown as listed below:

$$\gamma_k^{m+1} = b_k^{m+1}\left(1-b_k^{m+1}\right)\sum_l \gamma_l^{m+2}X_{jk}^{m+1} \tag{10}$$

Finally, the subsequent update solution for the hidden layer weights is shown:

$$X_{kj}^M \leftarrow X_{kj}^M - \rho\frac{\partial F_e}{\partial X_{kj}^M}$$

$$= X_{kj}^M + \gamma b_j^m b_k^{m+1}\left(1-b_k^{m+1}\right)\sum_l \gamma_l^{m+2}X_{jk}^{m+1} \tag{11}$$

In conclusion, the forward propagation will be determined prior to the practice deficit. Each layer's characteristics will be changed in the backpropagation technique in compliance with specific needs based on the loss [14].

4. Implementation and Results

A collection of MRI images from the online Kaggle platform was employed to train and test the network. As observed in Figure 4.1, the training dataset comprises 495 images missing a tumor alongside glioma lesions 838, meningioma cancers 833, and pituitary tumors 839. As observed in Figure 4.2, the study dataset contains 106 images without also a tumor, meningioma tumor 116, pituitary tumor 75, and glioma tumor 200.

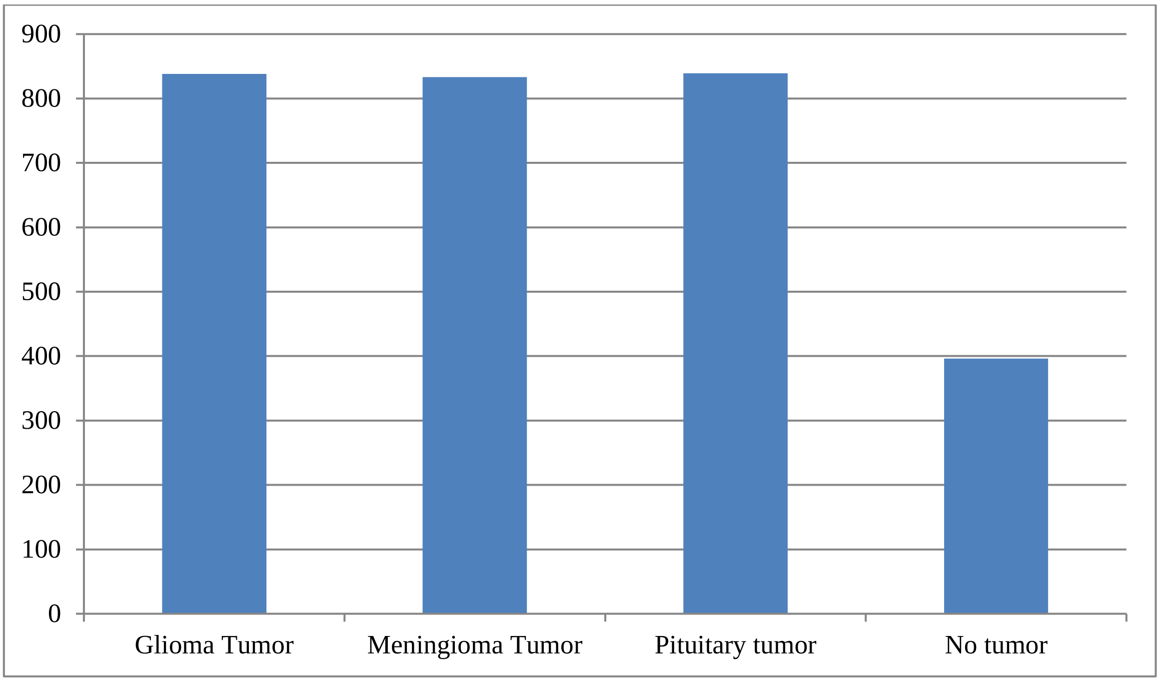


Fig. 4.1. Exercise data circulation

Fig.4.2. Testing data distribution

The MRI images undergo normalization during the preprocessing phase.

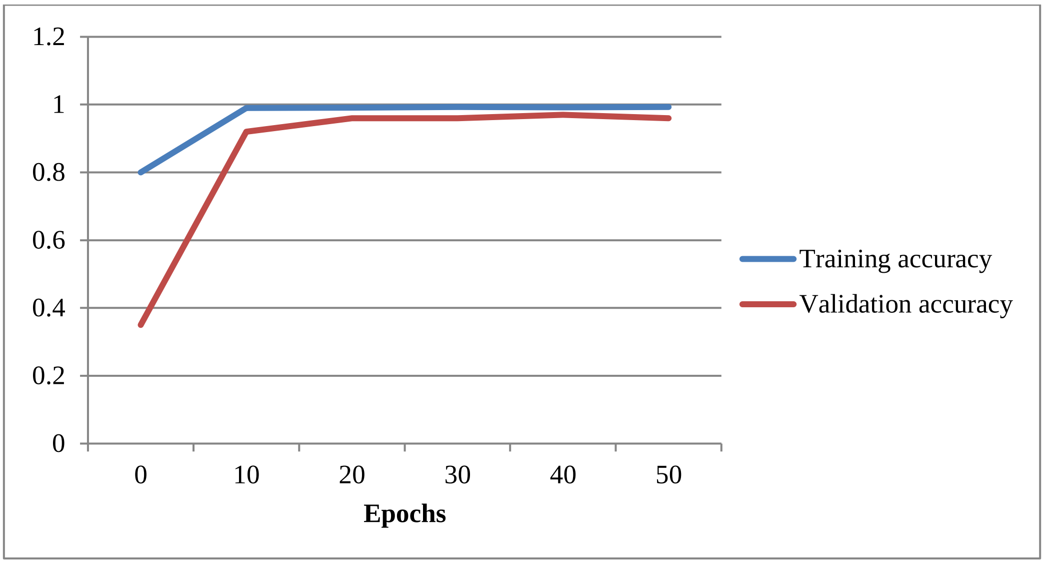
$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN'}$$

$$Precision = \frac{TP}{TP + FP'}$$

$$Recall = \frac{TP}{TP + FN'}$$

$$F1\ score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

To raise the accuracy rate, data augmentation was performed ahead of training. The amounts for True Positive, True Negative, False Positive, and False Negative pixels are referred to as TP, TN, FP, and FN, respectively. The accuracy and loss variability overtraining and validation procedure with EfficientNetB0 and EfficientNetB1 DL algorithms is illustrated in Figures 4.3 and 4.4.



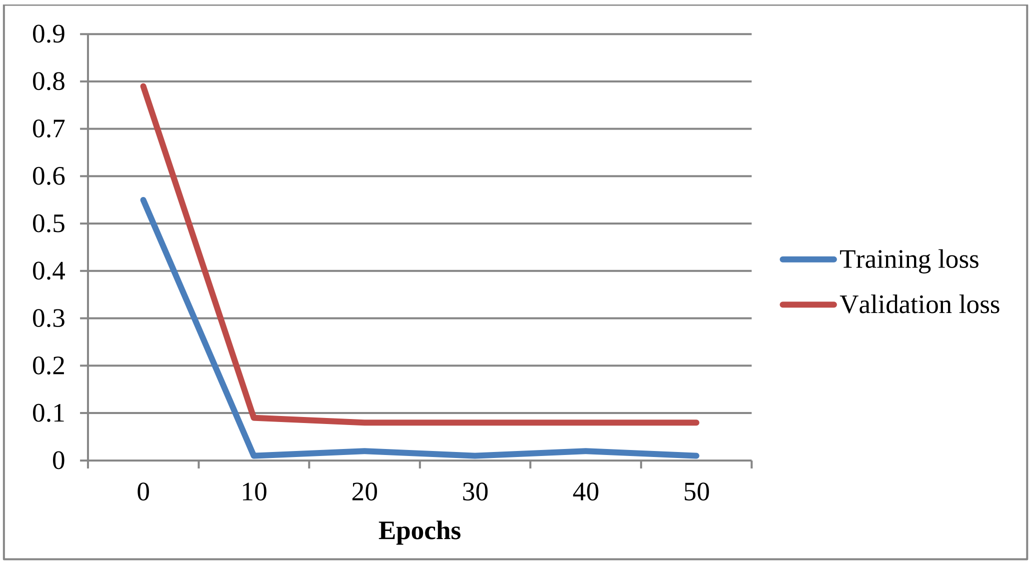
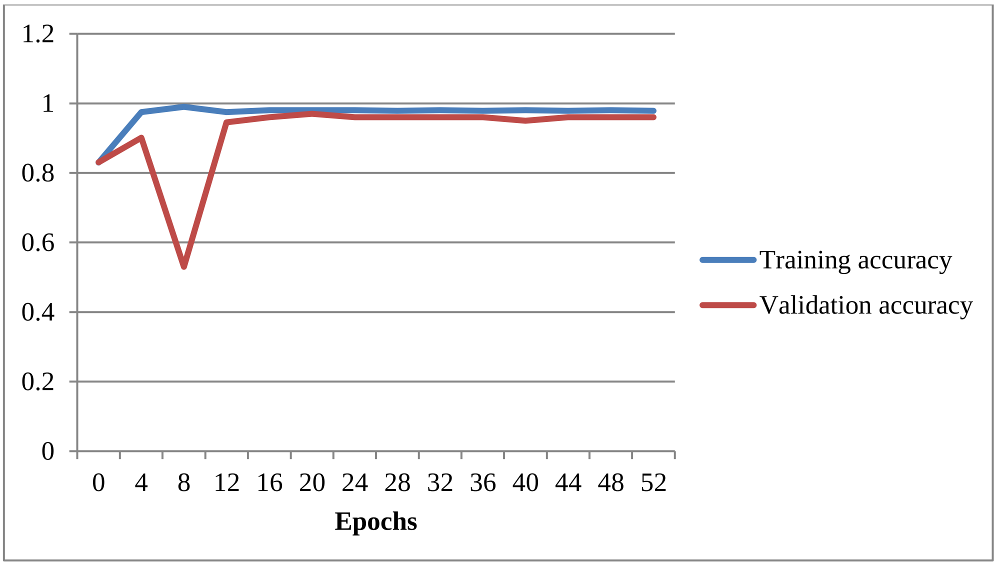


Fig. 4.3. Accuracy and loss are graphically shown with the EfficientNetB1 Model



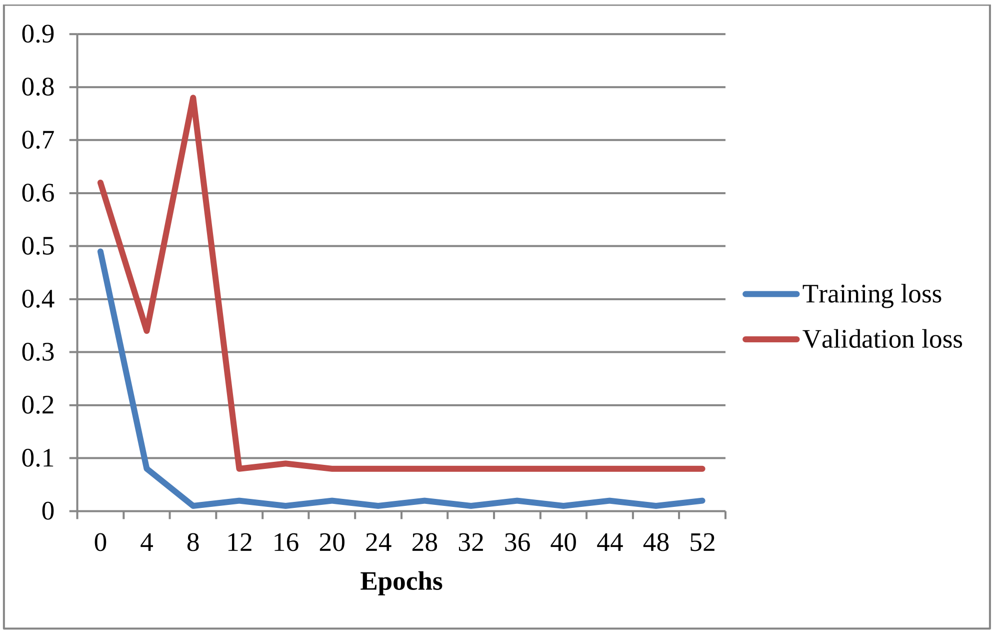


Fig. 4.4. Accuracy and loss of graphic representation using the EfficientNetB0 model

Table 1 illustrates the model's results. The recommended approach achieves 98% accuracy. We separated the recovery of MRI images of brain cancers into training and testing sections for our studies. We applied data augmentation to enhance our dataset by making slight modifications to our MRI examinations and then retrieving these upgraded images from our advised CNN model. We trained the model for 50 epochs with a batch size of 32. Both Keras and TensorFlow packages were implemented in the Python experiment. By polishing a pre-trained model, we had the chance to explore the total number of parameters. In contrast to the existing strategies, our claimed model yields good MRI outcomes that employ several data augmentation tricks as depicted in Figure 4.5. For more clarity, Table 2 further illustrates an identical contrast. Utilizing the revised EfficientNetB0 model, we attained an overall accuracy of 98% in an experiment employing the brain tumor dataset. The CNN's reasonably satisfactory results, even with little datasets, demonstrate the feature representation strengths of CNN [15].

Table 1. Projected Classic Results

Model	Glioma tumor				Meningioma tumor				Accuracy
	Precision	Recall	F1 Score	Support	Precision	Recall	F1 Score	Support	
Efficient B1	0.99	0.92	0.95	94	0.93	0.99	0.96	97	98
Efficient B0	0.99	1.0	0.98	94	0.98	0.97	0.97	97	99
Model	Pituitary tumor				No tumor				Accuracy
	Precision	Recall	F1 Score	Support	Precision	Recall	F1 Score	Support	
Efficient B1	1.0	0.98	0.98	88	0.99	1.0	0.98	52	97
Efficient B0	0.99	1.0	0.98	88	0.99	1.0	0.98	52	98

Table 2. Comparison of outcomes

	[31]	[32]	[35]	[44]	Proposed Model
Accuracy	91.67	95.2	91	98.4	99

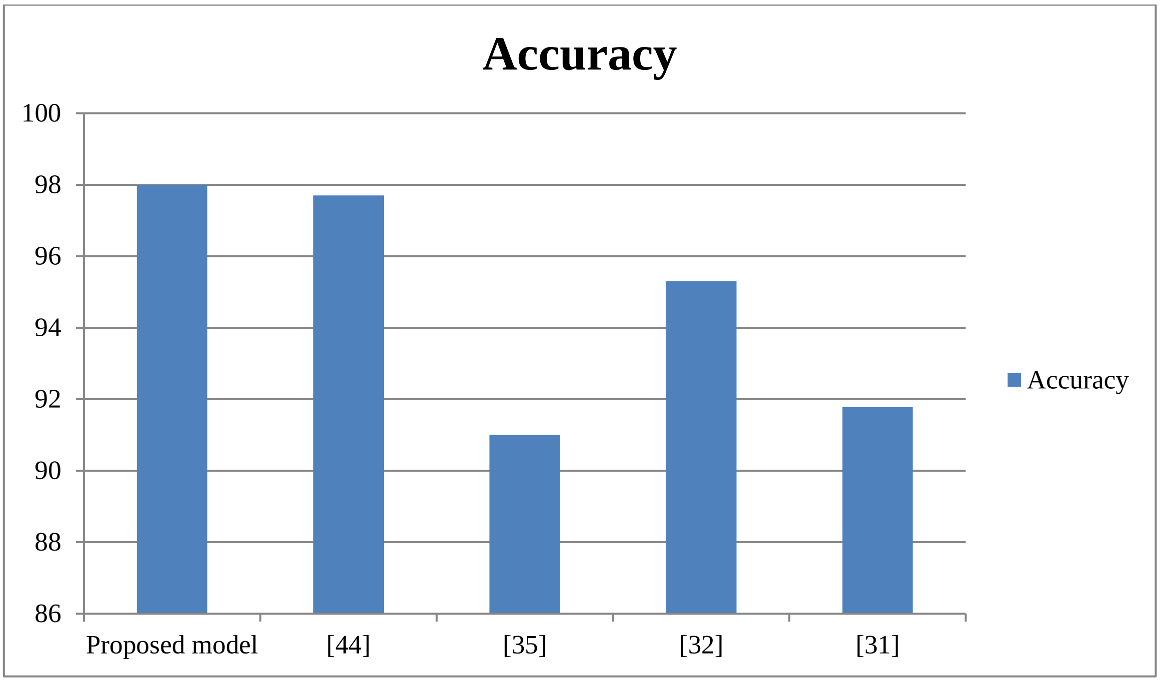


Fig. 4.5. Results Assessment

5. Conclusion

We developed a computerized approach for detecting brain lesions. The usefulness of the model relies on very accurate feature extraction and appropriate metric learning. By implementing transfer learning techniques and CNN model efficiency, we managed to retrieve the features. Since the EfficientNetB0 model's foundation is more extensive and suitable for feature extraction concerning localization and identification of particular facts from the data, we chose it for this study. Small datasets desire to make use of pre-trained deep learning models built with the transfer learning procedure, notably in the arena of healthcare imaging. On the other hand, deep learning networks (DL networks) have been employed in the field to deal with several different obstacles, such as pathology detection and the synthesis of PET photos from MRI images and vice versa. Consequently, this article presents a description of the advancement of deep learning, describes the elements of deep neural networks, and attempts to list the important steps essential to bring a supervised DL application into existence. Additionally, DL is unquestionably an advantageous and entertaining tool, but as is the case with various other methods, there are several kinds of execution-related difficulties that would be addressed when utilizing these models. The efficiency of brain tumor assessments has improved as a result of the preprocessing implementation of a frequency range data augmentation approach. The training time develops progressively with the number of iterative epochs, demonstrating that utilizing fewer epochs might end up in time benefits. Nevertheless, the accuracy of classification behaves independently of the depth architectures and the number of iterations. Although CNN is so true, surgeons can identify the source, measurement, and seriousness of tumors, which supports them in establishing an efficient treatment strategy.

References

[1] Yaqub, M., Jinchao, F., Arshid, K., Ahmed, S., Zhang, W., Nawaz, M. Z., & Mahmood, T. (2022). Deep learning-based image reconstruction for different medical imaging modalities. *Computational and Mathematical Methods in Medicine*, *2022*.

[2] Zhang, Y., & An, M. (2017). Deep learning-and transfer learning-based super resolution reconstruction from single medical image. *Journal of healthcare engineering*, *2017*.

[3] Adegun, A. A., Viriri, S., & Ogundokun, R. O. (2021). Deep learning approach for medical image analysis. *Computational Intelligence and Neuroscience*, *2021*, 1-9.

[4] Zambrano-Vizuete, M., Botto-Tobar, M., Huerta-Suárez, C., Paredes-Parada, W., Patiño Pérez, D., Ahanger, T. A., & Gonzalez, N. (2022). Segmentation of medical image using novel dilated ghost deep learning model. *Computational Intelligence and Neuroscience*, *2022*.

[5] Jiang, G., Ding, J., & Ge, C. (2022). Deep Learning-Based CT Imaging to Evaluate the Therapeutic Effects of Acupuncture and Moxibustion Therapy on Knee Osteoarthritis. *Computational and Mathematical Methods in Medicine*, *2022*.

[6] Manikanthan, S. V. (2021). Implementation and design of wireless IoT network using deep learning. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, *12*(3), 563-572.

[7] Kavitha, G., Prakash, C., Alhomrani, M., Pradeep, N., Alamri, A. S., Pareek, P. K., & Alhassan, M. (2023). Noise Estimation and Type Identification in Natural Scene and Medical Images using Deep Learning Approaches. *Contrast Media & Molecular Imaging*, *2023*.

[8] Huang, R., Zhou, Z., Wang, X., & Cao, X. (2022). Magnetic Resonance Imaging Features on Deep Learning Algorithm for the Diagnosis of Nasopharyngeal Carcinoma. *Contrast Media & Molecular Imaging*, *2022*.

[9] Tajbakhsh, N., Jeyaseelan, L., Li, Q., Chiang, J. N., Wu, Z., & Ding, X. (2020). Embracing imperfect datasets: A review of deep learning solutions for medical image segmentation. *Medical Image Analysis*, *63*, 101693.

[10] Zhang, J., Xie, Y., Wu, Q., & Xia, Y. (2019). Medical image classification using synergic deep learning. *Medical image analysis*, *54*, 10-19.

[11] Bhattacharya, S., Maddikunta, P. K. R., Pham, Q. V., Gadekallu, T. R., Chowdhary, C. L., Alazab, M., & Piran, M. J. (2021). Deep learning and medical image processing for coronavirus (COVID-19) pandemic: A survey. *Sustainable cities and society*, *65*, 102589.

[12] Ghnemat, R., Alodibat, S., & Abu Al-Haija, Q. (2023). Explainable Artificial Intelligence (XAI) for deep learning based medical imaging classification. *Journal of Imaging*, *9*(9), 177.

[13] Hebbale, S., Marndi, A., Kumar, B. M., Mohan, B. R., Achyutha, P. N., & Pareek, P. K. (2022). A survey on automated medical image classification using deep learning. *International Journal of Health Sciences*, *6*(S1), 7850-7865.

[14] Torres-Velázquez, M., Chen, W. J., Li, X., & McMillan, A. B. (2020). Application and construction of deep learning networks in medical imaging. *IEEE transactions on radiation and plasma medical sciences*, *5*(2), 137-159.

[15] Humayun, M., Khalil, M. I., Alwakid, G., & Jhanjhi, N. Z. (2022). Superlative Feature Selection Based Image Classification Using Deep Learning in Medical Imaging. *Journal of Healthcare Engineering*, *2022*.