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Automatic Diagnosis of Traumatic Brain Injury Using Deep Learning with CT scan Images

Behrang Rezvani Kakhki[1], Hosein Zakeri[2], Sayyed Majid Sadrzadeh[1], Seyed Mohammad Mousavi[1], Elnaz Vafadar Moradi[1], Golnoush Shahraki[3*]

1. Department of Emergency Medicine, Faculty of Medicine, Mashhad University of Medical Sciences, Mashhad, Iran.
2. Clinical Research Development Unit, Shahid Hasheminejad Hospital, Mashhad University Of Medical Sciences, Mashhad, Iran.

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A B S T R A C T

Introduction: Traumatic brain injury (TBI) results from external mechanical forces to the head, leading to brain dysfunction. The severity of injury significantly impacts patient health outcomes. Rapid and accurate diagnosis is essential for timely clinical intervention. Computed Tomography (CT) scans are currently the primary imaging modality for identifying intracranial injuries. However, manual analysis of CT images is time-consuming and highly dependent on radiologists' expertise.

Material and Methods: This study proposes an automated approach for detecting intracranial hemorrhage and skull fractures using Convolutional Neural Networks (CNNs). CT scan images containing various pathologies were collected from the Picture Archiving and Communication System (PACS). The dataset was divided into two classes: pathological and non-pathological. Images were resized to 128 × 128 pixels to reduce computational complexity and split into training (90%) and validation (10%) sets. Pre-trained ResNet18 and ResNet34 models were employed for classification. Evaluation metrics such as accuracy, precision, recall, and F-score were computed using a confusion matrix.

Results: The CNN model achieved an accuracy of 0.94, a precision of 1.0, and a recall of 0.88 in classifying CT images.

Conclusion: These findings indicate that CNN-based models can assist radiologists in faster and more consistent diagnosis of traumatic brain injuries. Further improvements may be achieved by increasing dataset size, refining preprocessing steps, and applying advanced optimization techniques to enhance generalization and robustness.

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Introduction

Traumatic brain injury (TBI) is a medical condition resulting from a unique combination of external or internal mechanical forces that directly impact the brain [1]. The severity of the injury increases with the strength of the applied force, leading to more significant health complications. TBI is a major cause of morbidity and mortality, with over 1.6 million people hospitalized annually in Europe and the United States due to this condition [2]. Individuals with a history of TBI often experience changes in decision-making processes, attention deficits, memory issues, impaired impulse control, increased aggression, and higher rates of suicidality [3,4,5]. These symptoms are more pronounced if the injury occurs during childhood [6,7].As noted, TBI can be caused by a blow to the head or by penetration injuries, such as those from bullets that fracture parts of the skull, leading to significant complications. Common causes of TBI include falls, vehicular accidents, sports injuries, and explosions. TBI typically requires immediate emergency medical evaluation and intervention to prevent further complications.

Computed tomography (CT) scans are typically the initial imaging procedure performed in the emergency setting for suspected traumatic brain injury. Utilizing a series of X-rays, CT scans provide detailed images of the brain, allowing for rapid identification of fractures, hemorrhages, hematomas, contusions, and brain tissue swelling. Magnetic resonance imaging (MRI), which employs strong radio waves and magnetic fields, is often conducted once the patient's condition stabilizes or if clinical symptoms persist. Swelling of brain tissue following a traumatic injury can elevate intracranial pressure and exacerbate brain damage. To monitor such pressure changes, physicians may insert a probe through the skull.

Clinical experts often use their extensive experience and tools like the Glasgow Outcome Scale (GOS) to predict patient outcomes with a high degree of accuracy [8].

**Corresponding Author:* Tel: +98-9019034430; Email: Golnoush.Shahraki@yahoo.com

The Glasgow Outcome Scale (GOS) has been utilized for over 40 years, significantly contributing to the advancement of understanding in brain injury assessments [8]. Physicians typically employ head CT scans to diagnose conditions such as bleeding, brain damage, and skull fractures in patients with head injuries. Currently, the CT scan is the standard for initial imaging and diagnosis of head trauma, providing comprehensive views by taking X-rays from multiple angles. These scans can quickly reveal bleeding, fractures, or other brain injuries. The low doses of radiation used in CT scans have not been shown to cause long-term harm. But for repeated scans, there may be a small increase in the lifetime risk of cancer.

Although manual approaches remain widely used for diagnosing and quantifying intracranial abnormalities, they are often labor-intensive and require physicians to thoroughly analyze patient imaging data [9]. To streamline this process, computer-assisted image analysis techniques have been introduced, offering valuable support in evaluating hematoma shape and volume, thereby expediting clinical decision-making. These methods, however, face persistent obstacles such as image noise inherent in CT scans, interference from bony structures, ventricles, or surrounding soft tissue swelling, and variability in hemorrhage characteristics like location, dimensions, brightness, and pixel distribution.In response to these limitations, numerous algorithms have been proposed for the segmentation, classification, and quantification of brain hemorrhages. Traditional hematoma segmentation methods include thresholding, region growing, level-set approaches, active contours, and fuzzy c-means (FCM). More recently, advanced techniques based on deep learning (DL) and neural networks (NN) have gained traction. These segmentation models are often paired with well-established classifiers such as support vector machines (SVM), decision trees, k-nearest neighbors (KNN), and k-means clustering to differentiate hematoma from non-hematoma areas or to classify various hematoma types [10].

Automatic analysis of TBI can significantly assist physicians in diagnosis [11]. Although artificial neural networks (ANNs) are often considered a "black box" in computational models, their potential in clinical medicine is vast, particularly in evidence-based practices, because ANNs can continually learn from new patient data [8]. This research aims to develop a deep learning algorithm using a convolutional neural network (CNN) to automatically detect key features in these images, such as intracranial hemorrhages and various types of fractures.In a 2018 study involving 30 head scan images from 20 imaging centers, researchers demonstrated that deep learning algorithms could accurately identify abnormalities in head CT scans that require immediate medical intervention [12]. Furthermore, a 2018 study utilized an ANN, a type of machine learning algorithm, to predict brain damage and achieved an accuracy of 97.98% [13].

Albert et al. [14] in 2016 utilized electroencephalography (EEG) data analysis for early diagnosis of TBI, achieving an accuracy of 87.85%. In 2021, another study evaluated and diagnosed mild traumatic brain injury (mTBI) using two models of simple and deep ANNs. The sensitivity and accuracy levels in the simple ANN model were 95.98% and 99.25%, respectively, while in the deep ANN model, they were 99.2% and 99.9%. The performance of these models demonstrated the feasibility of using ANNs for diagnosing mTBI [15].

In 2001, ANNs were employed as a nonlinear modeling technique to predict abnormalities in head CT scan images. In this application, the ANN model achieved a sensitivity of 82.2%, which was higher than the physician's prediction at 62.2% [16].

Grewal et al. [17] proposed a Recurrent Attention DenseNet (RADnet) architecture for detecting intracranial hemorrhages from 3D imaging data. Mansour et al. [18] developed a deep learning (DL) model for detecting and classifying intracranial hemorrhages (ICH) by integrating optimal image segmentation with the Inception v4 network. A persistent challenge in training hematoma segmentation systems lies in the extensive manual annotation required for large CT scan datasets. Nag et al. [19] employed a U-Net model to segment the brain into left and right hemispheres, subsequently identifying the deformed midline (dML) by tracing the interface between the two regions.

In 2013, researchers designed a classification approach for traumatic brain injury by extracting optimal feature vectors from CT brain scans to differentiate between mild and severe cases. They utilized a fully anisotropic Morlet wavelet transform to analyze the images and extracted coefficient energy values as texture features. To identify the most relevant features, genetic algorithms were applied using two fitness functions: classification error from (1) K-nearest neighbor (KNN) and (2) support vector machine (SVM) models. The resulting system achieved promising performance, with an accuracy rate of 86.5% [20].

Chen et al. [21] presented an automated system primarily based on computed tomography (CT) images. They employed Support Vector Machines (SVMs) to predict intracranial pressure (ICP) levels, which could serve as a rapid pre-screening tool for physicians. This tool aids in making decisions about whether to recommend invasive ICP monitoring.

Tu et al. [22] employed artificial intelligence (AI) and machine learning (ML) techniques to develop predictive models aimed at evaluating clinical outcomes in patients with traumatic brain injury (TBI) admitted to the emergency department. Their approach involved the application of six ML algorithms—logistic regression (LR), random forest (RF), support vector machine (SVM), LightGBM, XGBoost, and multilayer perceptron (MLP)—to construct and validate the performance of the proposed models [22].

The purpose of this study is to develop and evaluate a deep learning-based approach, specifically using convolutional neural networks (CNNs), for the automatic detection of Traumatic Brain Injury from CT scans. This method aims to enhance diagnostic accuracy, reduce the time required for manual analysis, and provide a reliable tool to assist healthcare professionals in clinical decision-making.

Materials and Methods

Dataset

This retrospective study was carried out between May 2022 and November 2023 and received ethical approval from the Ethics Committee of Mashhad University of Medical Sciences (IR.MUMS.MEDICAL.REC.1401.440). Owing to its retrospective design, the requirement for informed consent was waived by the committee. CT scan images were retrieved from the hospital's Picture Archiving and Communication System (PACS) and classified under the supervision of a specialist physician into two categories: scans exhibiting pathology and those without detectable abnormalities. It is worth noting that subjects were selected entirely at random, without consideration of demographic variables such as age or gender.

A random number is one selected from a defined or undefined set, exhibiting no predictable pattern. Typically, such numbers are statistically independent of one another. In this study, each participant in both groups was assigned a numerical identifier, and random integers were then generated using the Google Random Number Generator. This tool is capable of handling very large integers, extending to several thousand digits.

All CT- Scan images investigated by five specialist physician for categorizing images into 'with pathology' and without pathology'. The criteria that they considered contain: 1) Epidural Hematoma, 2) Subdural Hematoma, 3)Subarachnoid Hemorrhage, 4)Intracerebral Hemorrhage, 5) Intraventricular Hemorrhage, 6) Skull Fracture.

The total number of images collected for this study was 600. Figures 1 and 2 illustrate the process of data collection and examples of CT scan images with and without pathology, respectively.

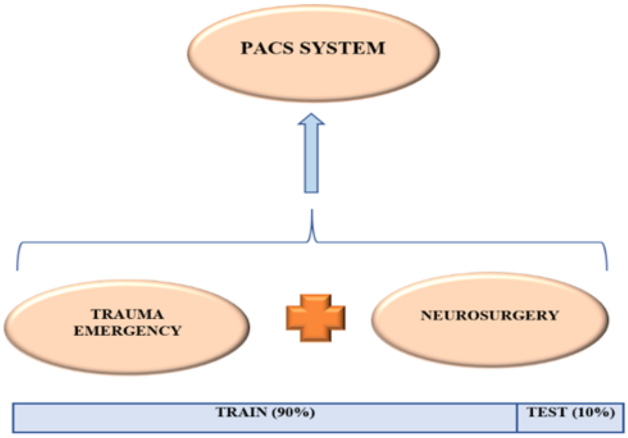

Figure 1. Simple process of the required data collection

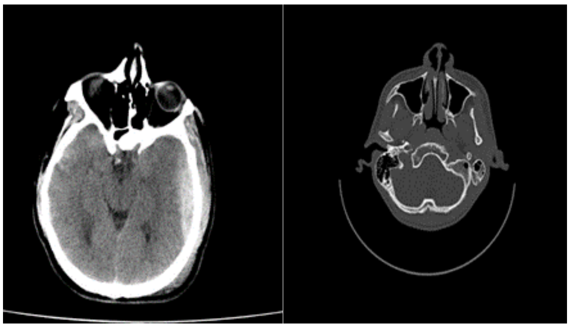

Figure 2. Two examples of CT scan images: (a) image containing pathology, (b) image without pathology

Convolutional Neural Network (CNN)

Neural networks are among the most widely used and effective methods in engineering applications today [23]. Machine learning (ML) methods serve as powerful tools to explore complex relationships. Since the early 1950s, these methods have been employed in medical sciences, where they have played a distinctive role [24]. The artificial neural network (ANN) is one of the principal methods used in this domain within ML [24]. ANNs are innovative computational methods for machine learning, knowledge representation, and utilizing the acquired knowledge to predict output responses from complex systems [24].

An ANN consists of a set of neurons that exchange signals through an interconnected network [25]. Each connection has a numerical weight that can be adjusted during network training to adapt the system to input patterns [25]. This weight reflects the connection strength between units [26]. In this study, we chose to utilize a convolutional neural network (CNN) to classify the images into two groups: those without pathology and those with pathology.

A convolutional neural network (CNN) is a well-known deep learning architecture inspired by the natural visual perception mechanisms of living organisms [27]. It can effectively represent the original image, enabling the recognition of visual patterns directly from raw pixels with minimal preprocessing. In other words, a CNN is a specialized type of feedforward neural network that autonomously learns features through the optimization of filters [28]. Feedforward neural networks are typically fully connected networks, meaning each neuron in one layer is connected to all neurons in the subsequent layer [29].

A fully connected layer in a neural network is one in which each neuron performs a linear transformation on the input vector using a weight matrix. This architecture ensures that every neuron is connected to all neurons in the preceding and succeeding layers, meaning that each element of the input vector contributes to the computation of every output element.

The rationale for selecting this method is that CNNs are specifically designed to perform effectively with matrix-structured inputs (two-dimensional, three-dimensional, and four-dimensional) without altering the structure of the input. Figure 3 presents our methodology. The convolutional layers pre-trained on the ImageNet dataset are transferred to the convolutional layers of the proposed model, which reduces the amount of data required for effective training. Task 1 involves a CNN model trained on the general-purpose ImageNet dataset, where Data 1 refers to the ImageNet images, Model 1 represents the convolutional layers, Head 1 denotes the fully connected layers, and Prediction 1 corresponds to the output labels [42]. In this framework, the knowledge gained from Task 1 (Model 1), facilitated by ResNet18 and ResNet34, is reused to enhance performance on a related domain-specific task in Task 2. Here, Data 2 consists of CT scan images, Model 2 again represents the convolutional layers (transferred from ImageNet), the New Head consists of custom fully connected layers, and Prediction 2 refers to the final predicted labels for the medical imaging task.

Transfer Learning

Transfer learning is a technique that leverages the knowledge from a model previously trained on one task (the primary task) to solve a related but different task. These two tasks are generally similar to a significant extent. Essentially, with transfer learning, we transfer the learned weights from a network trained on task A to enhance the learning process on task B. The primary advantage of using this technique is that it mitigates the need for large amounts of training data, which is particularly beneficial because training extensive models on vast datasets requires substantial computational power [31].

ResNet18 and ResNet34 are usually pre-trained on large datasets such as ImageNet. These models learn features such as edges, textures, shapes, and objects that are generalizable to different tasks.

The goal in training the model is to retain the broadly useful representations learned by the pretrained network, leverage them to solve our specific task, and adjust them only as necessary for task-specific adaptation. Fine-tuning involves initializing the added linear layers with trainable weights that are optimized for the new task, while preserving the integrity of the pretrained layers. To achieve this, only the weights of the newly added final layers are updated, while the weights of the remaining network are kept fixed—a process known as freezing the pretrained layers. When constructing a model from a pretrained network, the pretrained layers are automatically frozen by default. Upon invoking the fine_tune method, two steps are performed:

- The newly added layers are trained for one epoch with all pretrained layers frozen.

- Subsequently, all layers are unfrozen, and the entire model is trained for the specified number of epochs (in this study, 10 epochs).

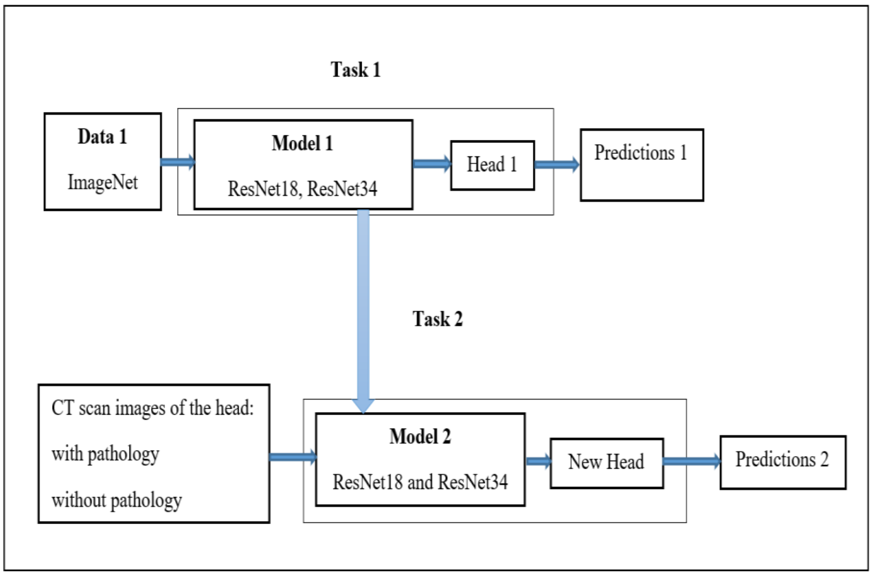

Figure 3. Block diagram of methodology

ResNet18 and ResNet34

Traditional deep learning networks consist of fully connected classification layers without any shortcut connections. The distinctive feature of ResNet architectures, compared to conventional networks, is the inclusion of shortcut connections that skip one or more layers. Essentially, these connections create a direct path from one layer to a later layer, effectively taking a "shortcut." Shortcut connection involves directly skipping one or more input layers and connecting them with subsequent layers.

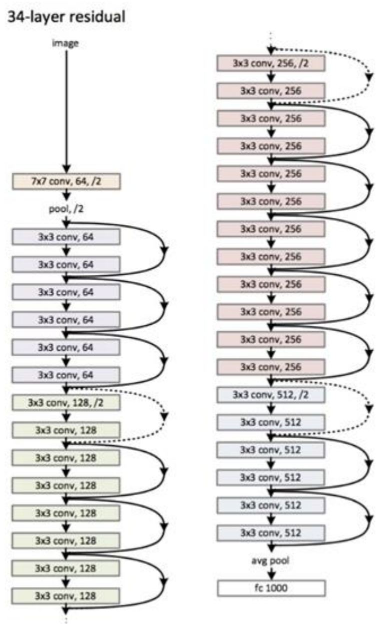

Figure 4. The block diagram of ResNet34

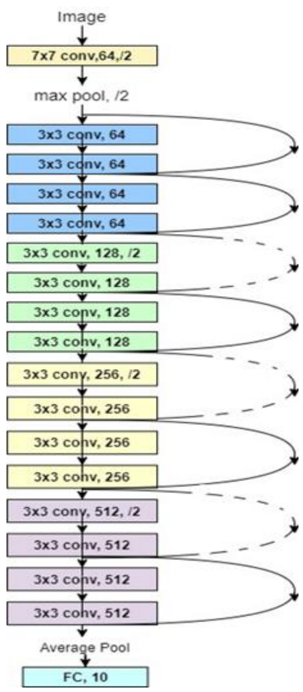

Figure 5. The block diagram of ResNet18

This architectural innovation addresses the vanishing gradient and exploding gradient problems often encountered in deeper layers of neural networks. In this study, we utilized ResNet18 and ResNet34. ResNet18 is a convolutional neural network (CNN) with 18 layers, designed to process images with an input size of 224 × 224 × 3 [30]. It starts with 64 neurons in the first layer and expands up to 512 neurons. ResNet34, on the other hand, is equipped with 34 layers (as illustrated in Figures 4 and 5).

Confusion Matrix

The confusion matrix is a fundamental evaluation tool in supervised machine learning, commonly employed to assess the performance of classification algorithms [32]. It is typically structured as a square matrix, where rows represent the actual classes and columns indicate the predicted classes [32]. Correct classifications appear along the diagonal of the matrix. In artificial intelligence, this matrix forms the foundation for calculating several performance metrics, including accuracy, precision, recall (sensitivity), and the F1-score—the harmonic mean of precision and recall (see Figure 6). Accuracy refers to the ratio of correct predictions to total samples, while precision is the proportion of true positive predictions among all predicted positives. These metrics were employed in this study to evaluate the model's effectiveness.

The confusion matrix operates based on a simple principle, where "T" denotes a correct (True) prediction and "F" denotes an incorrect (False) one. As shown in Figure 7:

True Positive (TP): Patients with pathology correctly identified as such.

False Negative (FN): Patients with pathology incorrectly identified as normal.

False Positive (FP): Normal patients incorrectly classified as having pathology.

True Negative (TN): Normal patients correctly identified as normal.

$$\text{Accuracy}: \frac{T_P + T_N}{T_P + F_P + F_N + T_N} \quad (1)$$

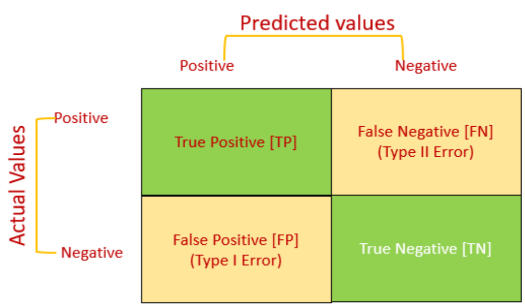

Figure 6. The block diagram of confusion matrix

Results

Given that injuries caused by head trauma are a significant factor in mortality, this study aimed to enable the timely diagnosis of traumatic brain injury (TBI) in challenging situations, such as physician fatigue, which leads to increased diagnostic errors, or in the absence of medical professionals, to prevent or minimize these issues and reduce uncertainties in diagnosis.

The CT scan images used in this study as input data were sourced from the Picture Archiving and Communication System (PACS).

To train the model, the data were randomly divided into two groups: training and testing, while ensuring the distribution and balance of each group of images were maintained. Specifically, 90% of the images were used for model training and 10% for testing.

Initially, after evaluating the evaluation metrics by confusion matrix and comparing the outputs of the convolutional neural network with a specialist physician's diagnosis, the accuracy rate for a dataset of 300 images was found to be 0.85. To enhance the efficiency and accuracy, we doubled the number of images in the dataset. After expanding the dataset, we observed an improvement in the accuracy of the neural network's outputs

between the two groups—normal individuals (without pathology) and patients with pathology—by 0.08, which means that the neural network's output accuracy reached 0.94. Figures 7 and 8 showed the confusion matrix of ResNet18 model and ResNet34 model, respectively.

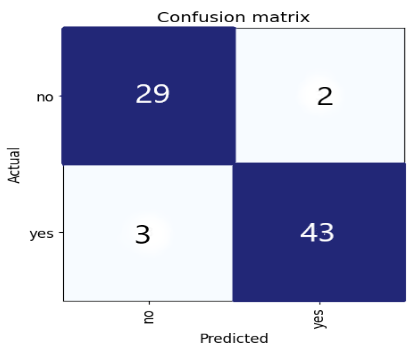

Figure 7. Confusion matrix for ResNet18 model

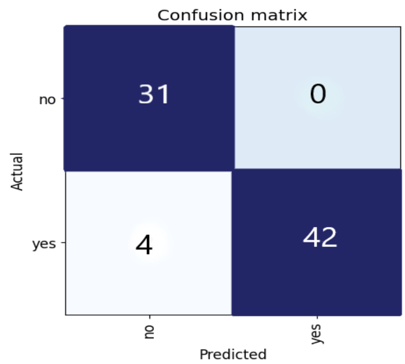

Figure 8. Confusion matrix for ResNet34 model

Precision is calculated as the ratio of true positives to the sum of true positives and false positives. For the ResNet34 model used in this study, the resulting precision after training was 1.0. Recall is formally defined as the proportion of correctly identified positive instances (true positives) to the total number of actual positive instances, comprising both true positives and false negatives. In this case, the Recall achieved by the ResNet34 model was 0.885714. The F1 Score, which represents the harmonic mean of precision and recall, provides a balanced measure of both metrics. Following training with ResNet34, the model achieved an F1 Score of 0.939391.

Tables 1 and 2 present the detailed performance of ResNet18 and ResNet34 at the last epoch with a dataset of 600 images. Comparison of table 1 and 2 shows that ResNet34 has a better performance after 9 epoch in this study. Figure 9 showed ResNet18 model and ResNet34 model accuracy. Figure 10 ,11 showed ResNet18 model and ResNet34 model train and validation loss.

Table 1. The evaluation metrics of the ResNet18 model

RESNET 18	
Train_Loss	0.310927
Valid_Loss	0.229992
Accuracy	0.935065
Precision	0.935483
Recall	0.906250
F-Score	0.92063
Confusion Matrix	$\begin{bmatrix}29 & 2\\3 & 43\end{bmatrix}$

Table 2. The evaluation metrics of the ResNet34 model

RESNET 34	
Train_Loss	0.306493
Valid_Loss	0.196720
Accuracy	0.948052
Precision	1.000000
Recall	0.885714
F-Score	0.939391
Confusion Matrix	$\begin{bmatrix}31 & 0\\4 & 42\end{bmatrix}$

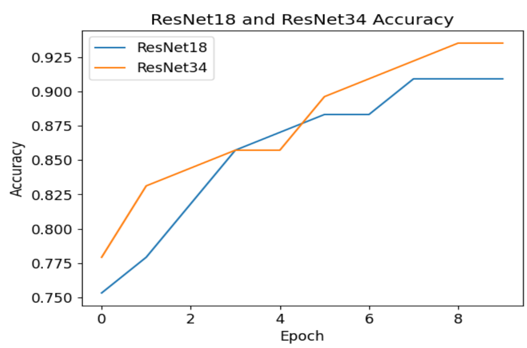

Figure 9. ResNet18 and ResNet34 accuracy

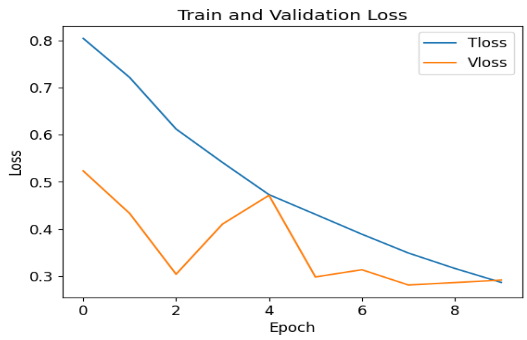

Figure 10. Train and Validation Loss in ResNet18 model

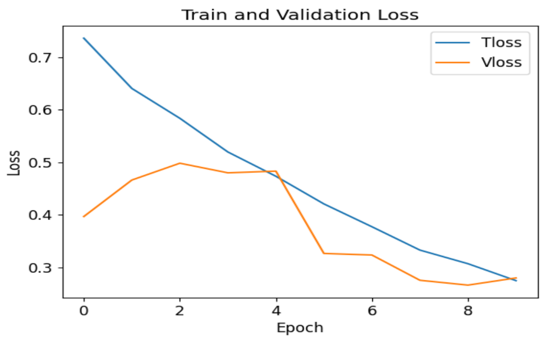

Figure 11. Train and Validation Loss in ResNet34 model

Figure 12. Two examples of classified CT scan images

Discussion

Extensive research has been conducted in the field of automatic diagnosis of brain injuries using various methodologies such as machine learning, deep learning, and artificial neural networks. The findings from these studies suggest that these methods can diagnose all types of brain injuries with high accuracy. Employing these techniques alongside clinical trials represents a significant advancement in diagnosing such injuries. Currently, many diagnostic approaches are evolving towards the integration of image processing and artificial neural networks.

The findings of this study underscore the pivotal role of dataset size in influencing the performance of artificial neural networks. A larger dataset enables the model to capture a broader range of features, thereby enhancing its ability to generalize and improving classification accuracy.In scenarios where only a limited number of labeled images are available, training a reliable model becomes challenging. Models trained on such small datasets are prone to overfitting or underfitting, resulting in suboptimal performance when exposed to real-world data.

One of the most effective strategies to address this limitation is transfer learning. Pretrained models such as ResNet18 and ResNet34, which have been trained on extensive and diverse datasets, offer robust feature extraction capabilities due to their deep and complex architectures. By leveraging these models and fine-tuning them for the target task, it is possible to achieve strong performance even with relatively small training datasets.

In this study, by employing the transfer learning technique and increasing the dataset size, we observed an improvement in accuracy.

Grewal et al. [17] diagnosed acute hematoma using a deep learning approach with a dataset of 329 images, achieving an accuracy of 0.818. Pappu et al. [33] developed a semi-automated method that segments brain parenchyma from cerebrospinal fluid (CSF) and computes the ratio of CSF volume to the total intracranial volume (csfv/icvv) to estimate intracranial pressure (ICP). The dataset size and accuracy in their study were 20 and 0.67, respectively [33].

Chen et al. [21] proposed a method for automated indirect midline shift (iML) detection where a vertical line is passed through the centroid of the image mass, and then the image is rotated to achieve the best symmetry. They used the Support Vector Machine (SVM) method with a dataset of 57 images, achieving an accuracy of 0.70.

Mansour et al. [18] utilized a deep learning approach and a multilayer perceptron for Intracranial Hemorrhage (ICH) detection and classification, with a dataset of 82 images and an accuracy of 0.941.

In this study, by using 600 CT scan images as input data and employing convolutional neural networks and the transfer learning technique, we achieved an accuracy of 0.948052. Compared to the studies mentioned, both the accuracy and the dataset size in our research are substantial. Additionally, the transfer learning technique addresses the neural network's need for extensive training data, which is crucial as training large models on vast datasets requires significant computational resources. In this study, we utilized ResNet18 and ResNet34. ResNet18 is a convolutional neural network (CNN) with 18 layers, designed to process images with an input size of 224 × 224 × 3 [30]. It starts with 64 neurons in the first layer and expands up to 512 neurons. ResNet34, on the other hand, is equipped with 34 layers. According to Table 2 in ResNet34, Accuracy, Precision, Recall, F-Score are respectively equal to: 0.948052 ,1.0, 0.885714, 0.939391, which is shown that ResNet34 with 34 layers is more successful to classifying than ResNet18.

Scholars have attained remarkable classification performance across diverse fields, such as medical imaging, satellite imagery analysis, and natural scene interpretation, by employing pre-trained ResNet34 models and adapting them to specific datasets through fine-tuning [34].

To further improve the neural network's precision, one could refine the image processing techniques applied or implement an optimization algorithm to derive the most salient features from CT scan imagery.

Conclusion

In this study, we utilized convolutional neural networks (CNNs) and applied the transfer learning technique along with ResNet18 and ResNet34 architectures. By increasing the number of CT scan images used as input data, we achieved an accuracy of 0.94 in classifying the images into two categories: normal individuals and patients with pathology.

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