Medical Image Classification of Brain Tumors using Convolutional Neural Network Algorithm

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Abstract—Brain tumor is a highly dangerous and deadly disease. It can occur due to the abnormal growth of cells or tissues in the head. Treatment for brain tumor is done with surgery and chemotherapy aimed at killing or destroying the cells that affect the growth process of brain tumor. Diagnosis of brain tumor is done using medical scans such as MRI, CT Scan, and PET Scan by analyzing the resulting images. Another method used to detect brain tumors is through biopsy, which is a process of taking cells or tissue from the body for examination in the laboratory. However, this method takes a long time because the cells taken from the patient will be examined in the laboratory. Therefore, a technique is needed to speed up accurate brain tumor diagnosis in order to obtain quick treatment. Machine learning can solve this problem with the classification of images produced by MRI. The classification technique that can be used is the GoogLeNet architecture in CNN. Because GoogLeNet is the algorithm that won the ImageNet Large Scale Visual Recognition Challenge (ILSVC) in 2014 The purpose of this study is to classify brain images using the GoogLeNet architecture. The dataset used in this study consists of 7023 images, consisting of 6320 images for training the model and 703 for testing the model. The results of this study obtained an accuracy percentage of 96%. This result is higher than previous studies that obtained an accuracy value of 94%.

Keywords: Brain Tumor; Classification; CNN; GoogLeNet; Machine Learning; MRI

1. INTRODUCTION

Brain tumors are one of the types of cancer that occur within the brain or its surrounding tissues. Brain tumors can be categorized into two main types: primary brain tumors and secondary brain tumors. Primary brain tumors occur when cells within the brain undergo mutations and proliferate uncontrollably. On the other hand, secondary brain tumors originate from cancer that has spread from other parts of the body and metastasized to the brain. [1]. The symptoms of a brain tumor can vary and may include headaches, nausea and vomiting, seizures, loss of balance, vision disturbances, as well as changes in behavior and personality. Brain tumors can be diagnosed through various methods, such as a CT scan, [2]. Magnetic Resonance Imaging (MRI), and biopsies. Following a diagnosis, the treatment for a brain tumor depends on the type, location, size, and stage of the tumor. The survival rate for brain tumors varies according to the type of brain tumor and the age of the patient [3][4]. Treatment for brain tumors may include surgery, radiotherapy, and chemotherapy. Surgery is typically performed to remove as much of the tumor as seen on medical images, while radiotherapy and chemotherapy can help destroy any remaining cancer cells after surgery. Although treatment can assist in controlling tumor growth, brain tumors can still have long-term effects on a patient's physical and mental health. Some side effects of treatment include fatigue, short-term memory loss, difficulty concentrating, and depression. Therefore, it is crucial for brain tumor patients to receive adequate support from their doctors, family, and friends. Additionally, some patients may also opt to seek support from support groups or therapists to help cope with the emotional impact of their condition.

Individuals affected by brain tumors experience a severe medical condition with a very high potential fatality rate [5]. This condition can lead to permanent damage to brain tissue, affecting bodily functions and mental health. Brain tumors can also compress surrounding areas, causing bleeding, swelling, and damage to nerves, which can affect the body's ability to function properly. Furthermore, brain tumors can spread to other areas in the brain or to other organs in the body, a process known as metastasis. Brain tumor metastasis to other organs, such as the lungs, bones, or liver, can result in serious damage and illness. Therefore, it is crucial to identify brain tumors as early as possible and initiate appropriate treatment to reduce the risk of complications and long-term health impacts on patients.

The management of brain tumors currently depends on the type, size, and location of the tumor, as well as the patient's health condition. There are several treatment options available to address brain tumors, including surgery, radiotherapy, chemotherapy, and molecular targeted therapy. Surgery is a procedure commonly performed to remove as much of the visible tumor as seen on medical images. Surgery can be done in two ways, either through a cranial incision or through the nose (endoscopy). During surgery, the doctor may also take tissue samples for diagnosis to confirm the type of tumor found. Radiotherapy uses X-rays or other high-energy particles to kill cancer cells. Radiotherapy can be administered after surgery or as the primary treatment. Newer radiotherapy techniques, such as stereotactic radiotherapy, can deliver higher doses of radiation to the tumor while minimizing radiation exposure to surrounding normal tissues. Additionally, brain tumor management can involve the use of chemotherapy. Chemotherapy entails the use of drugs to kill cancer cells. Chemotherapy can be administered through infusion, injection, or pills. Beyond medical treatment, patients can receive support from their doctors,
Detecting a brain tumor is a crucial step in ensuring an accurate diagnosis and initiating appropriate treatment. There are several medical imaging techniques used to detect brain tumors, including MRI [6], CT Scan, PET Scan, and Biopsy. MRI is a non-invasive imaging test that uses a magnetic field and radio waves to produce detailed images of the brain. MRI allows doctors to visualize the size, location, and shape of the tumor in great detail and differentiate between the tumor and normal brain tissue. CT Scan is an imaging test that uses X-rays to create three-dimensional images of the brain [7]. CT Scan can assist doctors in visualizing the tumor, its location, and size. Positron Emission Tomography (PET) scan is an imaging test that uses a radioactive substance to generate images of the brain. PET scans can help doctors observe the level of activity in the brain's cells, including cancer cells. Biopsy is a procedure in which a tissue sample is taken from the suspected tumor area for microscopic analysis. Biopsy can help doctors confirm the diagnosis of the tumor and determine its type. Once a brain tumor is detected, doctors can begin appropriate treatment to reduce the risk of complications and long-term health impacts on the patient. Early intervention can also improve the chances of recovery and the patient's quality of life.

The detection of brain tumors using machine learning is an increasingly promising and evolving technology. Machine learning is a branch of artificial intelligence that enables machines to learn from data and make intelligent predictions or actions based on patterns or past experiences. In this context, machine learning can be used to assist doctors in detecting brain tumors more quickly and accurately. One example of using machine learning to detect brain tumors is by leveraging MRI technology. With machine learning, MRI images can be processed rapidly and interpreted by machines with a high level of accuracy. Machine learning algorithms can learn from labeled MRI image examples and then be used to predict whether a new MRI image contains a brain tumor or not. Furthermore, machine learning can also be used to analyze other data related to brain tumors, such as genomic and clinical data. Genomic data can provide information about genetic changes in cancer cells, which can help doctors choose more precise and effective treatments. Clinical data, on the other hand, can offer insights into a patient's health history, symptoms, and other risk factors that may impact the prognosis and management of a brain tumor. The use of machine learning in brain tumor detection has the potential to enhance the speed and accuracy of diagnosis and assist doctors in selecting the most appropriate and effective treatments for patients. We offer an artificial intelligence algorithm because this algorithm can help in diagnosing brain tumors accurately based on model training to recognize the type of brain tumor.

Research on classification methods in machine learning has been conducted using various images. A study [8] used CNN and Faster R-CNN algorithms to classify breast cancer diseases, achieving an accuracy of 91.26% with CNN and 63.89% with Faster R-CNN. The study concluded that the CNN algorithm is superior to the Faster R-CNN algorithm. CNN can classify various images, as in the research [9] that classified grapevine leaf diseases using grapevine leaf images. This research employed the K-Means Clustering, VGG16, and CNN algorithms. The dataset consisted of 4000 grapevine leaf images categorized into four classes: leaves with black measles, leaf spots, healthy leaves, and leaf blight. The research yielded an accuracy of 99.50% in the training model and 97.5% in the test data. However, this research focuses on agriculture, not disease diagnosis. Research using brain images has also been conducted employing the CNN algorithm. The dataset included 3064 images categorized into four classes: glioma, no tumor, meningioma, and pituitary. The research achieved accuracies of 91.9% [10] and 93.68% [11]. Based on the previous research studies mentioned, this study aims to classify brain tumor images using the GoogLeNet algorithm to compare the accuracy with previous research that used CNN algorithms for brain tumor image classification. GoogLeNet is one of the CNN algorithms designed by the Google Research team in 2014 [12]. This architecture is well-known for its efficient use of the Inception module to extract features from input images. Inception itself is a collection of convolution and pooling layers connected in parallel and then merged at the output.

2. RESEARCH METHODOLOGY

Image processing using deep learning is highly prevalent today. Many classification methods can be employed for image classification, but one of the most commonly used is the CNN algorithm [13]. The CNN algorithm is one of the popular algorithms in the field of deep learning [14], which is why this research utilizes CNN for classifying brain tumor images. The stages conducted in this study are outlined in Figure 1, the research stages.

Figure 1. Research Methods
Figure 1 shows the most crucial part of the dataset in this research. The dataset is a highly influential research material, and the accuracy of the results is greatly impacted by the number of datasets used for training, as a larger dataset can lead to higher accuracy levels. In this study, the dataset consists of 7,023 brain tumor images categorized into four classes: glioma, no tumor, meningioma, and pituitary. The dataset was obtained on the Kaggle website. The dataset varies in size, requiring a method to resize the images to a consistent size for classification using the CNN algorithm [15]. The image resizing process can be performed in the Preprocessing stage [16]. The preprocessing stage is an initial data processing step for text, video, or image data to prepare the data before processing it with a specific model or algorithm. The purpose of preprocessing is to enhance the quality [17] or relevance of data by eliminating parts of the data that contain irrelevant information for the research. In this study, preprocessing is carried out using the resizing technique. Image resizing is the process of changing the dimensions of a digital image by enlarging or reducing its pixel dimensions. The image sizes used in this research are depicted in Figure 2.

Figure 2. Preprocessing image (a) before (b) after

In Figure 2, it can be observed that the size of the digital image before preprocessing is 520x520. However, after preprocessing, the image size is reduced to 150x150 because the images used in this study are resized to 150x150 before being input into the CNN algorithm. This size is significantly smaller than the original image size. However, important information in the image is not lost, as shown in Figure 2, where image 2(a) and image 2(b) appear indistinguishable to the human eye. The next step after preparing the digital image data is to train the dataset based on the CNN algorithm used. The CNN algorithm consists of feature extraction and fully connected layers. Feature extraction is the process in which CNN learns important patterns in the image, such as lines, angles, or other complex shapes that help recognize objects or characteristics in the digital image being studied [18]. The layers in the feature extraction phase consist of convolution and pooling layers. The convolution layer is the first layer that processes the input image. The input image is transformed into binary data in the form of a matrix to facilitate the convolution process. 1 3x3 filter, where each of the digital image passes through the kernel or filter to be convolved, resulting in a new matrix called a feature map. The more kernels used to extract image matrices, the more feature maps are generated. An example of the convolution process in CNN can be seen in Figure 3.

Figure 3. Convolution process (a) image matrix (b) kernal (c) feature map

Figure 3(a) represents an image matrix with a 3x3 image size, resulting in a 3x3 matrix. The matrix in Figure 3(a) is of size 5x5 because it underwent convolution with zero padding. Zero padding is a technique that involves adding zero values to the edges of the input image before the convolution operation. This is done to preserve information at the image's edges. In Figure 3(a), you can see that the edges of the matrix are filled with zeros, expanding the image from its original 3x3 size to 5x5, with the addition of 1 matrix on each edge, filled with zeros. Figure 3(b) represents the kernel used, which is a 2x2 kernel with values 1, 2, 3, and 4. These values are multiplied with the input image matrix. The results of these multiplications are summed, and the sum is placed in a new matrix, which serves as the output image to be used as input for the next operation. Each kernel moves horizontally from left to right. The movement of the kernel depends on the algorithm used, typically with a Stride (s) of 1, meaning the kernel moves 1 pixel to the right. The output image from the convolution stage becomes the input image for the pooling layer. The pooling layer is a critical component of the CNN architecture used to reduce the dimensionality of the image or feature map generated by the convolution layers. There are typically two types of pooling methods: MaxPooling and AveragePooling.
of pooling in the pooling layer: max pooling, which selects the highest value, and average pooling, which takes the average of the values in the kernel matrix used. The convolution and pooling layers can be repeated before moving on to the classification stage in the fully connected layer. Feature maps generated from the pooling layer are fed into the fully connected layer for classification according to the provided classes. The model testing stage is the most crucial step in this research, as it is carried out to evaluate the algorithm used. Algorithm testing is conducted using equation (1) [19][20] [21].

\[
\text{Accuracy} = \frac{\sum \text{TP}}{\text{Total Data}}
\]  

(1)

The value of TP (true positive) represents the total number of data correctly classified according to the labels provided for each image. The TP value is obtained after the algorithm is tested using previously unseen testing data. The total data used for testing the algorithm amounts to 703 images, which consist of glioma, no tumor, meningioma, and pituitary images. The accuracy percentage obtained is analyzed to draw conclusions about the research related to brain tumor image classification using the GoogLeNet algorithm in CNN.

3. RESULT AND DISCUSSION

This research was conducted using the Python programming language with the Jupyter Notebook text editor. The brain tumor image dataset was downloaded from the Kaggle website, consisting of 7,023 images, categorized into three brain tumor disease classes: glioma, meningioma, and pituitary, and one class of images without brain tumor disease, called the no-tumor class. The downloaded images had large and varying pixel dimensions, so they were resized to 150x150 pixels. Large-dimensional images can affect the algorithm's processing speed in image extraction for classification, as the kernel would require more time to convolve the images. The preprocessing steps in this research included the resizing technique and converting three-dimensional (RGB) images into two dimensions (grayscale). Once the images were prepared, they were input into the algorithm for training and learning image patterns. The training process used 6,032 (90%) images categorized into the four brain tumor classes. The training data was divided into 32 data batches. Batch size represents the number of data samples processed together in one iteration during model training. Using batch size offers advantages such as speeding up the model training process and optimizing the hardware's memory usage. It efficiently updates model parameters and doesn't require storing the entire training data in memory simultaneously. Additionally, CNN utilizes the softmax activation function. The softmax function is used to convert the output layer's values into probabilities for each target class. It takes an input vector and produces an output vector with the same number of elements, where each element of the output vector represents the probability that the input belongs to a specific class. Softmax converts the numerical vector produced by the preceding layer into an interpretable probability distribution. The algorithm was trained using the training data, repeatedly providing the data to learn the patterns in each image. Training was conducted for 20 epochs, which means the classification was tested 20 times. The results of the classification of the training data can be seen in Figure 4.

Figure 4 displays the results of the model training using 6,032 images. In the first iteration, an accuracy of 27% was achieved with a loss of 130%. The low initial accuracy and high loss value in the first iteration are because the model is just starting to learn the data, and further training is required. In the second iteration, the accuracy improved to 63%, representing a substantial increase compared to the first iteration, while the loss decreased. In the third iteration, there was another increase in accuracy, reaching 71%, and the loss reduced to 61%. This indicates that the model used for brain image classification had already significantly improved in accuracy. This improvement continued until the 20th iteration. In the final iteration, the algorithm successfully achieved an accuracy of 97% with a loss of 8%. These results demonstrate that there is a substantial increase in
accuracy with each iteration of the training dataset. Therefore, it can be stated that the more iterations performed, the higher the accuracy achieved in training the model. Based on these results, the average accuracy obtained during training the dataset is calculated to be 87%. Following is table 1 model training results.

<table>
<thead>
<tr>
<th>Epoch</th>
<th>Loss</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.3</td>
<td>0.27</td>
</tr>
<tr>
<td>2</td>
<td>0.85</td>
<td>0.63</td>
</tr>
<tr>
<td>3</td>
<td>0.61</td>
<td>0.71</td>
</tr>
<tr>
<td>4</td>
<td>0.47</td>
<td>0.81</td>
</tr>
<tr>
<td>5</td>
<td>0.38</td>
<td>0.83</td>
</tr>
<tr>
<td>6</td>
<td>0.28</td>
<td>0.89</td>
</tr>
<tr>
<td>7</td>
<td>0.25</td>
<td>0.91</td>
</tr>
<tr>
<td>8</td>
<td>0.24</td>
<td>0.91</td>
</tr>
<tr>
<td>9</td>
<td>0.18</td>
<td>0.93</td>
</tr>
<tr>
<td>10</td>
<td>0.21</td>
<td>0.92</td>
</tr>
<tr>
<td>11</td>
<td>0.21</td>
<td>0.92</td>
</tr>
<tr>
<td>12</td>
<td>0.14</td>
<td>0.94</td>
</tr>
<tr>
<td>13</td>
<td>0.09</td>
<td>0.96</td>
</tr>
<tr>
<td>14</td>
<td>0.1</td>
<td>0.96</td>
</tr>
<tr>
<td>15</td>
<td>0.12</td>
<td>0.96</td>
</tr>
<tr>
<td>16</td>
<td>0.07</td>
<td>0.97</td>
</tr>
<tr>
<td>17</td>
<td>0.08</td>
<td>0.96</td>
</tr>
<tr>
<td>18</td>
<td>0.08</td>
<td>0.97</td>
</tr>
<tr>
<td>19</td>
<td>0.09</td>
<td>0.96</td>
</tr>
<tr>
<td>20</td>
<td>0.08</td>
<td>0.97</td>
</tr>
</tbody>
</table>

The trained algorithm has learned various patterns in the studied images, allowing the model to be tested to obtain testing model accuracy values. Model testing is conducted by providing previously unseen testing data. There are 703 testing data consisting of glioma, no tumor, meningioma, and pituitary classes. The results of the testing are presented in a confusion matrix for ease of interpretation. The confusion matrix for the testing model’s results is displayed in Figure 5.

![Confusion Matrix](image)

**Figure 5.** Confusion Matrix

Based on the values in the confusion matrix, the following TP (true positive) values are determined: glioma 157, no tumor 201, meningioma 166, and pituitary 151. The results of the confusion matrix calculations are presented in Figure 6.

<table>
<thead>
<tr>
<th>precision</th>
<th>recall</th>
<th>f1-score</th>
<th>support</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.98</td>
<td>0.92</td>
<td>0.95</td>
</tr>
<tr>
<td>1</td>
<td>1.00</td>
<td>0.99</td>
<td>0.99</td>
</tr>
<tr>
<td>2</td>
<td>0.91</td>
<td>0.95</td>
<td>0.93</td>
</tr>
<tr>
<td>3</td>
<td>0.95</td>
<td>0.97</td>
<td>0.96</td>
</tr>
</tbody>
</table>

accuracy 0.96 703
macro avg 0.96 0.96 0.96 703
weighted avg 0.96 0.96 0.96 703

**Figure 6.** Results of Confusion Matrix Calculations
Figure 6 displays the values of Precision, Recall, and F1-Score. Precision is one of the evaluation metrics used in classification modeling. Precision measures how well the model successfully identifies the true positive values compared to the total results predicted as positive. Precision can be calculated using equation (2).

\[
\text{Precision} = \frac{TP}{TP+FP}
\]

The average precision value obtained is 96%. Recall, in a confusion matrix, is one of the evaluation metrics used in classification modeling. Recall measures how well the model successfully identifies all true positive cases compared to the total number of positive cases that should have been identified. Recall can be calculated using equation (3).

\[
\text{Recall} = \frac{TP}{TP+FN}
\]

The average recall value obtained is also 96%. Meanwhile, the F1-score is an evaluation metric that is useful in classification modeling, as it combines precision and recall. The F1-score measures the balance between precision and recall, providing a more comprehensive picture of the classification model's performance. The F1-score is expressed as the harmonic mean of precision and recall and can be calculated using equation (4).

\[
F_1 - \text{Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}
\]

The obtained F1-Score value is 96%. Furthermore, the resulting confusion matrix allows for accuracy testing of the model used. Below is Table 2, displaying the results of the model testing.

<table>
<thead>
<tr>
<th>Index</th>
<th>Classes</th>
<th>Total of Data</th>
<th>True</th>
<th>False</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>glioma</td>
<td>170</td>
<td>157</td>
<td>13</td>
</tr>
<tr>
<td>1</td>
<td>notumor</td>
<td>203</td>
<td>201</td>
<td>2</td>
</tr>
<tr>
<td>2</td>
<td>meningioma</td>
<td>174</td>
<td>166</td>
<td>8</td>
</tr>
<tr>
<td>3</td>
<td>pituitary</td>
<td>156</td>
<td>151</td>
<td>5</td>
</tr>
</tbody>
</table>

The results of the model testing, as presented in Table 2, successfully classified the Glioma class with 157 out of 170 total Glioma images correctly classified, achieving an accuracy rate of 92.35%. However, there were 13 misclassified images, accounting for 7.65% of the Glioma class. The No Tumor class exhibited the highest accuracy rate, with 201 images correctly classified out of a total of 203, resulting in a 99% accuracy rate. For the Meningioma class, the model correctly classified 166 images out of 174, yielding an accuracy rate of 95.4%. Nevertheless, there were 8 misclassified images in this class. Meanwhile, the Pituitary class achieved an accuracy rate of 96.79%, with 151 images correctly classified out of the total number of Pituitary images. The lowest accuracy results were observed in the Glioma class, with 10 out of 13 misclassified images. In these instances, the algorithm mistakenly classified these images as Meningioma, while they actually belonged to the Glioma class. The glioma class had a larger error because 10 meningioma images considered the glioma class.

\[
\text{Accuracy} = \frac{675}{703} = 0.96
\]

Based on these results, the visualization of the accuracy obtained can be seen in Figure 7.
compared to previous research on brain tumor classification using brain tumor images, which reported accuracies of 91.9% [10] and [11] 93.68%.

4. CONCLUSION

The research, utilizing the CNN algorithm with the GoogLeNet architecture, achieved an accuracy rate of 96%. The highest accuracy was observed in the "notumor" class, with a percentage of 99%. These results demonstrate that the model effectively recognizes images without brain tumors, minimizing the likelihood of misdiagnosing brain tumor diseases. In conclusion, the GoogLeNet architecture can be employed to classify brain tumor diseases using images obtained from MRI scans. These findings highlight the potential of GoogLeNet architecture in the field of healthcare for diagnosing brain tumor diseases. However, it's worth noting that there was a 4% error rate in classifying brain tumors. Future research endeavors should aim to improve accuracy to 100% to eliminate errors in diagnosing brain tumor diseases.

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