A design of a brain tumor classifier of magnetic resonance imaging images using ResNet101V2 with hyperparameter tuning

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ABSTRACT

Brain tumors are a disease that is quite dangerous and requires severe treatment. One thing that is quite important is the process of diagnosing the brain tumor. This diagnosis process requires intense attention, and differences in interpretation may arise. Machine learning has been used in several fields, including disease diagnosis. This paper proposes an intelligent diagnostic tool for brain tumors using ResNet101v2. ResNet101V2 is used to classify meningioma, glioma, pituitary, and normal from magnetic resonance imaging (MRI) images. This research includes data collection, data preprocessing, ResNet101v2 design and evaluation. We investigate three models of ResNet101v2 for brain tumor classification. The best model achieves an accuracy of 96.2%.

Keyword

Brain tumor
Deep learning
Magnetic resonance imaging
ResNet101V2
Transfer learning

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1. INTRODUCTION

The brain is a vital organ and acts as the center of intelligence, interpreter of the senses, control of body movements, and behavior controller. This organ has hundreds of billions of interconnected cells through trillions of connections. Brain tumor is deadly because of its aggressive nature, heterogeneous characteristics, and low survival rate. Therefore, this brain tumor needs to be identified as early as possible. This identification can then be followed up with therapy appropriate to the type of brain tumor. This encourages the need to develop methods for classifying brain tumors. Classification of brain tumors is conducted by considering their location, texture, shape, and aggressiveness [1]–[5].

Brain cancer treatment depends on how accurate the diagnosis of the tumor is. A definitive diagnosis of a brain tumor can be made by histopathological examination via biopsy. Another supporting examination is a computed tomography (CT) scan or magnetic resonance imaging (MRI) of the head. Lateralization of ictal interictal temporal lobe hypoperfusion in lesional and non-lesional temporal lobe epilepsy using arterial spin [6]–[9]. Human diagnosis requires years of special training and good stamina and concentration. Therefore, an intelligent brain tumor classification system is needed [10]–[12]. Machine learning or artificial intelligence has been applied to several applications [13]–[17]. Brain tumor MRI image classification has been carried out using convolutional neural networks (CNN) [18]–[22]. This study proposes a classification system of brain tumors using ResNet101V2 from MRI images [23]–[25].

Journal homepage: http://ijai.iaescore.com
This paper is then written in the following structure. First, section 2 describes the research method in detail. Then, the results and discussion are described in section 3, including the performance of the ResNet101V2 model. Section 4 concludes the paper.

2. RESEARCH METHOD

Figure 1 shows a system of the brain tumor classifier of MRI images using ResNet101V2. The system consists of data collection and processing, and the ResNet101V2 model is used as the classifier. Data preparation includes data labeling and cleaning.

![Diagram of brain tumor classifier of MRI images using ResNet101V2](image)

**Figure 1. Brain tumor classifier of MRI images using ResNet101V2**

### 2.1. Data collection and processing

The data used in this research is MRI images with a resolution of 512x512. The data distribution of the dataset is listed in Table 1. The data used in this research is from Sardjito General Hospital, Figshare, SARTAJ, and Br35H datasets \[26, 27\]. Data from Sardjito General Hospital was collected from ten patients diagnosed with various types of brain tumors. The data from Sardjito General Hospital consists of 18 meningiomas from three patients, six pituitaries from one patient, and 28 gliomas from five patients \[28, 29\]. Figshare, SARTAJ, and Br35H datasets comprise 1645 meningioma, 1621 glioma, 1757 pituitary, and 2000 normal.

<table>
<thead>
<tr>
<th>Class</th>
<th>Training data</th>
<th>Validation data</th>
<th>Test data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Meningioma</td>
<td>1765</td>
<td>207</td>
<td>105</td>
</tr>
<tr>
<td>Pituitary</td>
<td>1615</td>
<td>190</td>
<td>96</td>
</tr>
<tr>
<td>Normal</td>
<td>1700</td>
<td>200</td>
<td>100</td>
</tr>
<tr>
<td>Glioma</td>
<td>1949</td>
<td>229</td>
<td>115</td>
</tr>
<tr>
<td>Total</td>
<td>7029</td>
<td>826</td>
<td>416</td>
</tr>
</tbody>
</table>

### 2.2. ResNet101V2

This research used Python programming with several libraries such as Pandas, NumPy, and TensorFlow \[30–32\]. We present three ResNet101V2 models in this paper. Table 2 lists the hyperparameter of the Resnet101v2 models.

<table>
<thead>
<tr>
<th>No</th>
<th>Name</th>
<th>Rotation range</th>
<th>Width shift range</th>
<th>Shear range</th>
<th>Zoom range</th>
<th>Learning rate</th>
<th>Trainable layer</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Model#1</td>
<td>40</td>
<td>0.20</td>
<td>0.20</td>
<td>0.20</td>
<td>0.001</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>Model#2</td>
<td>30</td>
<td>0.15</td>
<td>0.15</td>
<td>0.15</td>
<td>Piecewise constant scheduling</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>Model#3</td>
<td>30</td>
<td>0.15</td>
<td>0.15</td>
<td>0.15</td>
<td>Piecewise constant scheduling</td>
<td>10</td>
</tr>
</tbody>
</table>

3. RESULTS AND DISCUSSION

#### 3.1. Model#1

Figure 2 shows the accuracy of model#1 on training and validation data. Model#1 has a training accuracy of 92.2%, validation accuracy of 92.4%, and test accuracy of 91.1%. Figures 3 and 4 show the receiver operating characteristic (ROC) and the confusion matrix of model#1 \[33–35\]. The meningioma class has the lowest accuracy, with an accuracy of 83.8%.

#### 3.2. Model#2

Figure 5 shows the training and validation accuracy of model#2. Model#2 has a training accuracy of 94.8%, validation accuracy of 93.2%, and test accuracy of 91.4%. Figures 6 and 7 show the ROC and the confusion matrix of model#2. The meningioma class has the lowest accuracy, with an accuracy of 81.9%, and
has the smallest area under the curve based on the precision-recall (PR) curve. Fluctuations decrease where the loss and accuracy values slope and will move towards a concurrent condition. The difference in loss values between training data and validation data increases, but the difference between validation and test data decreases. Model#2 has unsatisfactory results because it is still below the research threshold of 95.0% but has resolved the problems in model#1.

Figure 2. Accuracy of model#1 [37]

Figure 3. ROC of model#1

Figure 4. Confusion matrix of model#1

Figure 5. Accuracy of model#2

Figure 6. ROC of model#2

Figure 7. Confusion matrix of model#2
3.3. Model#3

Figure 8 shows the training and validation accuracy of model#3. Model#3 has a training accuracy of 98.4%, validation accuracy of 96.9%, and test accuracy of 96.2. Figures 9 and 10 show the ROC and the confusion matrix of model#3. Table 3 compares the performance of the three models of ResNet101v2.

![Figure 8. Accuracy of model#3](image)

![Figure 9. ROC of model#3](image)

![Figure 10. Confusion matrix of model#3](image)

Table 3. Performance of ResNet101V2 models

<table>
<thead>
<tr>
<th>Model type</th>
<th>Training time (s)</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Training</td>
<td>Validation</td>
</tr>
<tr>
<td>Model#1</td>
<td>4086</td>
<td>92.2</td>
</tr>
<tr>
<td>Model#2</td>
<td>4045</td>
<td>94.8</td>
</tr>
<tr>
<td>Model#3</td>
<td>4687</td>
<td>98.4</td>
</tr>
</tbody>
</table>

4. CONCLUSION

This paper presented our proposed brain tumor classification system from MRI images using ResNet101v2. Our work includes data collection, processing, model training, and evaluation. ResNet101v2 has been successfully applied as a tool for classifying brain tumors based on the results of MRI images. The experimental results show that our best model achieved a training accuracy of 98.4%, validation accuracy of 96.9%, and test accuracy of 96.2%.

ACKNOWLEDGMENTS

We thank Universitas Gadjah Mada for the facilities provided for this research.
REFERENCES


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