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# High-Accuracy Stroke Detection System Using a CBAM-ResNet18 Deep Learning Model on Brain CT Images

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**Abstract**

Stroke is a brain dysfunction that occurs suddenly as a result of local or overarching damage to the brain, lasts for at least 24 hours, and causes about 15 million deaths each year globally. Immediate medical treatment is essential to reduce the potential for further brain damage in stroke patients. Medical imaging, especially computed tomography (CT scan), plays a crucial role in the diagnosis of stroke. This study aims to develop and evaluate a deep learning architecture based on Convolutional Block Attention Module (CBAM) and ResNet18 for stroke classification in CT images. This model is designed through data preprocessing, training, and evaluation stages using a cross-validation approach. The results showed that the CBAM-ResNet18 integration resulted in a high accuracy of 95% in distinguishing stroke and non-stroke cases. The accuracy rate reached 96% for nonstroke identification (class 0) and 94% for stroke (class 1), with recall rates of 96% and 93%, respectively. Outstanding classification ability is demonstrated by an Area Under the Curve (AUC) value of 0.99. In comparison, the standard ResNet18 model shows significant fluctuations in validation loss and difficulty in generalization, with training accuracy only reaching 64-68%. On the other hand, CBAM-ResNet18 showed a significant performance improvement with a validation accuracy of 95%, a validation loss of 0.0888, and good generalization on new data. However, the limitations of the dataset and the interpretation of the results indicate the need for further validation to ensure the generalization of the model. These results show the great potential of the CBAM-ResNet18 architecture as an innovative tool in stroke diagnostic technology based on CT imaging analysis. This technology can support faster and more accurate clinical decision-making, as well as open up opportunities for further research related to the development of artificial intelligence-based systems in the medical field.

*Keywords:* Deep Learning, ResNet, Brain Stroke, Computed Tomography, Image Analysis.

## 1. Introduction

Stroke is a prevalent and serious condition that demands immediate attention. It can be identified by various clinical signs, including temporary paralysis or weakness on one side of the body (hemiparesis), challenges with speaking or comprehending language (aphasia), numbness in the face, arms, or legs (typically on one side), visual disturbances (such as blurred or lost vision), and issues with coordination or balance. In more critical cases, symptoms may escalate to unconsciousness or even result in death [1]. Stroke is predicted to be the leading cause of death by 2030, accounting for about 14.4% of total deaths, and is the third leading cause of loss of DisabilityAdjusted Life Years (DALY), about 6% per cent, in middle-income countries [2]. Nationally, the prevalence of stroke in Indonesia increased from 7 per 1000 population in 2013 to 10.9 per 1000 population in 2018 [3]. With timely treatment and optimal prevention, side effects and stroke deaths can be minimized. One of the main keys to treating stroke is early diagnosis of accurate. In

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this case, the radiological modality of Computerized Tomography Scanning (CT Scan) of the brain plays a central role [4]. CT scan is the most important diagnostic tool for detecting intracerebral abnormalities in patients with clinical symptoms of stroke. The results of a CT scan of the head can determine the location with a detailed visualization of brain structures and can reveal abnormalities such as intracranial hemorrhage or ischemia associated with stroke [5]. The information is invaluable in diagnosing stroke and determining its type and severity. When dealing with a stroke emergency situation, doctors usually use CT scans to get a clear picture of the patient's condition. However, manually analyzing CT images requires a lot of time and expertise. This is a problem because time is precious in dealing with stroke cases that require quick action. Therefore, researchers have been looking for solutions to help doctors recognize strokes from CT images more quickly and accurately. This breakthrough comes from the field of artificial intelligence, specifically deep learning algorithms [6],[7].

Deep learning is a machine learning concept based on artificial neural networks. For many purposes, deep learning models outperform shallow machine learning models and traditional data analysis approaches [8]. In recent years, deep learning based on convolutional neural networks (CNNs) has been successfully applied in the diagnosis of various diseases, such as skin cancer [9] and lung disease [10] and lung disease [11]. This CNN model has demonstrated the possibility of automatically extracting features from images, thus completing the task of feature selection and weight adjustment without the need for complex stages of image processing and pattern recognition [12]. However, there are still some challenges in the classification of brain images CT scans. Traditional deep learning often struggles to recognize complex and specific patterns associated with stroke abnormalities in these highly heterogeneous datasets [13]. As a result, the accuracy of the classification becomes unstable and less reliable. To address this challenge, the researchers are trying to harness the power of deep learning, a branch of artificial intelligence inspired by the way the human brain works. In this study, they combined two powerful deep learning approaches, namely Residual Network (ResNet) architecture and Convolutional Block Attention Module (CBAM). ResNet is a well-known deep learning model for processing images at various scales, while CBAM is a module that helps neural networks concentrate on important features in images [14]. By combining these two approaches, the resulting system is diverted to better extract important information from brain CT scan images, even from very diverse data sets. The main goal of this study is to develop a deep learning system based on ResNetCBAM that is able to detect stroke cases with high accuracy from brain CT scan images. The initiative aims to harness the potential of deep learning to address real-world challenges in medical image analysis. By changing the variation of aging data and focusing on relevant features, it is hoped that this system will help doctors in making more accurate and faster diagnoses, thereby increasing the chances of effective stroke treatment.

## 2. Literature Review

Recent studies have explored a variety of deep learning architectures to address challenges in medical image analysis. For example, a study by [15] It uses deep convolutional networks, artificial neural networks, to describe the area affected by ischemic stroke. They adopt a supervised approach, training the network with pre-marked data. In particular, they implemented the activation function of the Leaky Rectified Linear Unit (Leaky ReLU) in the last two layers of the network. This innovation allowed the network to capture features not found in the UNet architecture, resulting in a Dice coefficient of 0.70, which indicates the effectiveness of the network in isolating ischemic stroke regions in CT scan images.

In the same vein, [16] performed image classification of brain tumors using three artificial neural network architectures: AlexNet, GoogLeNet, and ResNet50. Among them, ResNet50 showed the highest accuracy at 85.71%, outperforming AlexNet and GoogLeNet in recognizing the type of brain tumor in this study. A study conducted by Zhang et al. showed that the ResNet-CBAM deep learning model can effectively distinguish benign and malignant lung nodules using CT images, morphological features, and clinical information. The ResNet-CBAM model achieved an AUC of 0.940 and an accuracy of 86.7% when using only images as input, and increased to an AUC of 0.957 with an accuracy of 89.8% after integrating morphological features and clinical data. These findings indicate that the integration of additional information in deep learning models can improve the accuracy of lung nodule diagnosis, thereby supporting better decision-making in clinical practice [17].

Further advances in neural networks were explored by Keun Ho Ryu and his team, as reported by [18]. They used three CNN models—CNN2, VGG16, and ResNet50—trained with transfer learning to classify CT images of the brain that were not enhanced. Their findings revealed that CNN2 and ResNet50 significantly outperformed VGG16, achieving an accuracy of 0.9872. Other studies by [19] apply a ResNet-based deep learning model to predict celiac disease by analyzing biopsy slides. Their models achieved 95.3%, 91.0%, and 89.2% accuracy for identifying celiac disease, normal tissue, and nonspecific duodenitis, respectively. In addition, the area under the receiver operating characteristic curve (ROC) exceeded 0.95 for all classes, demonstrating the model's strong performance in disease detection.

In the field of stroke diagnosis, [20] proposed a deep learning method that combines ResNet50 with a dense layer to detect intracranial hemorrhage in NCCT brain images. Using 1164 brain images from 62 patients with hemorrhagic stroke, their model achieved remarkable results with 99.6% accuracy, 99.7% specificity, and 99.4% sensitivity, outperforming ResNet50 alone. This breakthrough has significant potential to improve the diagnosis and management of hemorrhagic stroke. Last [21] Addressing the problem of illegal images polluting the internet, which can negatively impact an individual's physical and mental health. To address this, they developed a model that integrates ResNet101 with CBAM's attention mechanism in residual neural networks. By adjusting the training parameters and optimization algorithms, they significantly improved the recognition accuracy of the system, achieving a classification accuracy of 93.2% in identifying illegal images.

## 3. Methodology

Stroke classification of brain CT scan images using deep learning is a technological breakthrough that combines artificial intelligence with medical science. This deep learning approach uses models to extract complex patterns and hidden features from raw image data. With this ability, stroke classification from CT scan at age can be carried out precisely and efficiently, even in cases that may go unnoticed by humans. To improve the accuracy in distinguishing stroke conditions from normal conditions, this study integrates the ResNet architecture with the CBAM. This combination aims to better capture complex features in brain imagery and their contextual relationships. In this way, the model's ability to accurately classify and identify various brain conditions can be significantly demonstrated. The procedures briefly discussed below involve the main stages of data collection and preprocessing, model training, and deep learning model testing.

### 3.1. Dataset

This dataset was obtained from the Kaggle platform, an online community that facilitates data exchange and collaboration for the purpose of artificial intelligence search and redevelopment. The data set used is a group compiled by Afridi Rahman in 2021 and is publicly available. Overall, the dataset consisted of CT images of the patient's brain, with a total of 2,501 images, of which 1,551 images were normal cases (non-stroke) and 950 images were brain stroke cases [22]. This dataset only groups the images into two main categories: stroke and non-stroke, with no further details on the type of stroke (such as ischemic or hemorrhagic). Information about the dataset curation process is also limited, so we cannot confirm the image selection criteria or their diversity based on patient demographics (age, gender, etc.). This is one of the limitations in our study, which can affect the generalization of the results.

### 3.2. Data Pre-Processing

The data preprocessing stage is essential to improve the quality and relevance of the information contained in the image, as well as to eliminate noise and artifacts. In this study, the entire preprocessing process was carried out using Google Colaboratory, a cloud computing environment that allows efficient execution of Python code. One of the challenges in processing image datasets is the diversity of image sizes and resolutions. To address this issue, all images in the dataset are resized to 224 x 224 pixels. This size is selected based on standards commonly used for the ResNet model architecture and offers a balance between preserving important details in medical images and computational efficiency [23]. Each image will be converted to RGB color mode (Red, Green, Blue) to ensure consistent color channel representation hate across all images. After this, the image is converted into a NumPy array, making it suitable for deep learning model input. The final step in preprocessing involves applying a median blur filter to each CT image. This filter reduces noise and irrelevant fine details that can interfere with the model's ability to identify significant features.

This filter was chosen because of its ability to remove such noise without blurring the edges, which is crucial in the analysis of brain structure on medical images Median blur is applied using the cv2.medianBlur(image, 5) function, with a kernel size of 5x5.

## 3.3. Deep Learning Model Architecture

### 3.3.1. Residual Network (ResNet)

ResNet is a neural network technology designed to enable the training of deep learning models with enormous depth. This architecture was created to address common problems in deep learning training, such as long training times and a limited number of layers [24]. The main idea behind ResNet is the use of residual connections that allow information to flow directly from one layer to the next. These residual connections help to overcome the problem of learning degradation in very deep networks, thus enabling effective training of deeper networks. The advantage of ResNet compared to other architectures is that its performance does not diminish as it deepens the architecture [25]. ResNet implementations involve connections passing through two to three layers containing ReLU and batch normalization between architectures. Research by [25] shows that ResNet performs better in image classification compared to other models, indicating that image features are well extracted by ResNet. They adopted residual learning applied to several layers. Reciprocal blocks in ResNet are defined as follows:

$$y = F(x_i W + x) \tag{1}$$

$x$ the input layer, $y$ is the output layer, $W$ is the weight matrix and $F$ function is represented by the residue map. In a ResNet architecture, a residual block can only be implemented if the input and output dimensions of each block are identical. The number of layers that make up each residue block depends on the ResNet variant used. For the ResNet18 and ResNet34 models, each residue block consists of two layers. Meanwhile, for the deeper ResNet50 and ResNet101 models, each residue block consists of three layers. In one study, ResNet 18 was used for classification tasks on CT scan images. Before being processed by the model, brain images are pre-processed by changing the resolution size to 224x224 pixels to be compatible with the ResNet architecture.

### 3.3.2. ResNetCBAM Model

In this study, we use the ResNet18-CBAM model architecture to improve the accuracy of stroke detection from CT scan images. This architecture consists of several main modules, namely the channel attention module and the spatial attention module, which function to highlight important features of the input data. Figure 1 shows the complete architecture of the ResNet18-CBAM model used in this study.

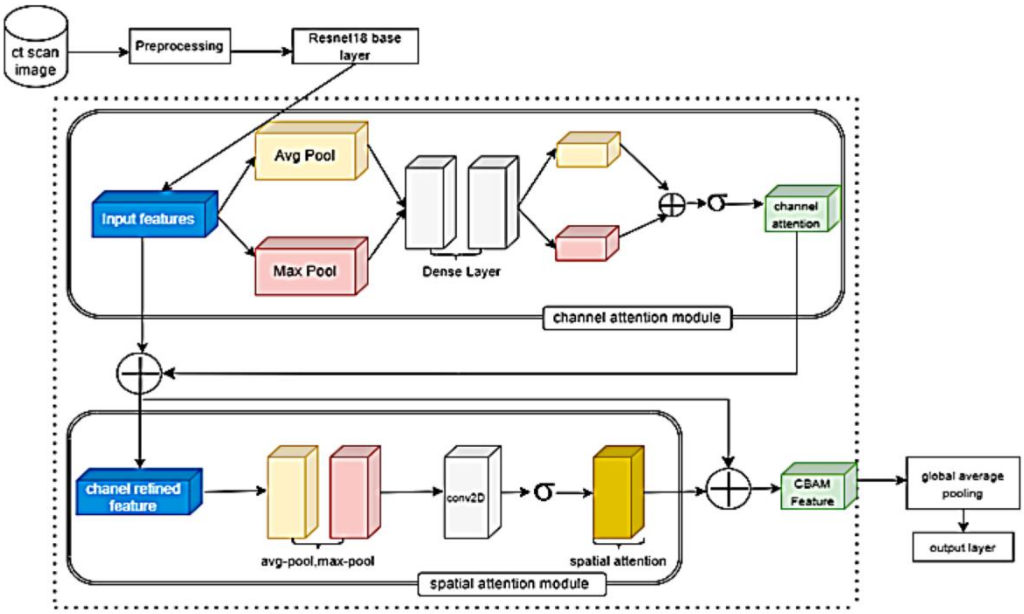


**Figure 1.** ResNet18CBAM model architecture

ResNetCBAM is a deep learning model that combines the ResNet architecture with CBAM on a tention module. This model is designed to improve the ability to detect relevant features of image data, especially in the task of detecting brain stroke from CT scans. In the ResNetCBAM model, the ResNet architecture used is ResNet18, which consists of 18 convolutional layers. In addition to the convolutional layer, ResNet18 also uses a batch normalization layer and a max collection layer to improve the performance and efficiency of the model. CBAM consists of two main attention mechanisms: Tractal Attention and Spatial Attention. Channel Atten allocates different attention to each channel in the feature map, allowing the model to focus more on the most informative channels. Meanwhile, al spatial attention places different attention to each spatial location in the feature map, allowing the model to focus more on the most relevant regions in the image. In the ResNetCBAM model, the CBAM module is integrated into the ResNet18 architecture in an efficient manner. After several layers of convolution and pooling in ResNet18, the feature map is fed to the CBAM module to implement the Channel Attention and Spatial Attention mechanisms.

The result is a modified feature map with greater weight of attention to the most relevant features and regions. These two attention mechanisms work together to improve the model's ability to capture and utilize meaningful information from the input image data. The feature extraction process begins by retrieving the output from the ResNet18 architecture, referred to as. The feature map has dimensions (number of channel), (height), and (width). Furthermore, the feature map is modified by combining the Channel Attention Map (CAM) and the Spatial Attention Map through the element wise multiplication operation (). The result of this operation is a modified feature map, in which the model can focus more on the features and regions that are most relevant for a particular task. Mathematically, this process can be expressed as:

$$\mathrm{R} = \mathrm{CAM} \odot \mathrm{F} \tag{2}$$

The feature map, denoted as $F$, represents the output that has been enhanced using the CBAM attention mechanism. Within this mechanism, the CAM plays a crucial role by indicating the relative importance of each channel in the feature map, allowing the model to focus on the most relevant features. The operation $R$ involves element-wise multiplication between the feature map $F$ and the two generated CAMs, effectively refining the feature representation and improving the model's ability to capture significant patterns.

With the CBAM attention mechanism that combines channel attention and spatial attention, the ResNetCBAM model can more effectively capture and utilize meaningful information from input image data, thereby improving the brain stroke detection performance of CT scans.

### 3.4. Model Evaluation and Validation

In developing a classification model, evaluating and validating the model's performance is a very important stage. To evaluate the performance of the model, it can be demonstrated with the help of accuracy, precision, recall and F1 Score obtained from the Confusion Matrix. Performance metrics can be measured from the Confusion Matrix as follows:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} \tag{3}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{4}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{5}$$

$$\text{F1 Score} = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision+Recall}} \tag{6}$$

TP is true positive, the TN is true negative, the FP is false positive, and the FN is false negative.

In addition to the confusion matrix, one of the methods that is often used to assess the performance of classification rules in classification problems is the ROC (Receiver Operating Characteristic) curve. In this curve, the x-axis indicates the ficity specification, while the yaxis indicates the sensitivity. Area under the curve (AUC) is a widely used measure to determine model performance on test data. If the AUC value is close to 1, it indicates that the model is performing very well [26].

## 4. Results and Discussion

In this study, 80 percent of the training dataset was used for training, while the remaining 20 percent was used for validation, and the test dataset was used for the ResNet50 CBAM model. The total dataset consisted of 2501 im ages, of which 1551 images were normal cases (non-stroke), and 950 images were brain stroke cases. To divide the dataset into training data and test data, a cascading random sampling technique is used. This approach ensures that the proportion of each class (normal and stroke) in the training data and the test data remains the same as the portion of the pros present in the overall data set. The initial dataset is randomized (random=True) to avoid potential bias in the data sequence. The distribution of data across training and testing datasets is presented in table 1, which details the separation for normal and stroke cases.

**Table 1.** Data Partition

| Separating Datasets | Usual | Stroke |
|---|---|---|
| Data Training | 1016 | 760 |
| Data Testing | 254 | 190 |

This division ensures that the class distribution in the training data and the test data represents the class distribution in the overall dataset.

### 4.1. Experimental Results

This study developed a ResNet18 deep learning model optimized with the CBAM to classify between stroke and normal conditions based on brain CT scan images. CBAM is an attention module that can guide the convolution model to focus more on informative areas/features and ignore less informative areas. This CBAM architecture is one of the highlights of this study. In addition to the ResNet18 model with CBAM, this study also trained the basic model of ResNet18 without CBAM for comparison purposes. The training of both models is shown in figure 2 and figure 3. First, we resize all the images to 224x224 pixels. After preprocessing, the model is trained using an iterative process called epochs, which is carried out over 15 epochs with each epoch consisting of 56 iterations or batches of data. The metrics evaluated are loss and accuracy. Loss is the value of the loss function used to measure how much error the prediction model has, while accuracy is the percentage of correct predictions made by the model. The evaluation was carried out on two types of data, namely training data and validation data.

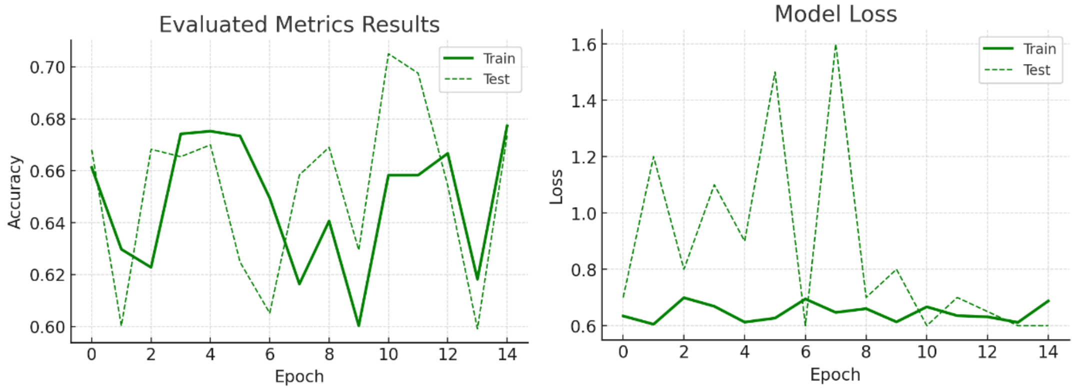


**Figure 2.** Evaluation of the ResNet Base Model18

In figure 2, the standard ResNet18 model shows symptoms of fluctuations in validation loss, indicating instability rather than obvious overfitting. Training accuracy continued to improve, reaching around 64-68%, but significant declines and spikes in validation losses suggest that the model struggled with generalizations. The validation accuracy did not consistently improve and showed sharp changes, indicating potential problems with the model's ability to generalize. Further tuning of hyperparameters or regularization may be necessary to stabilize training and improve overall performance. On the other hand, in figure 3, the performance of the ResNet18 model with CBAM improves significantly in terms of both accuracy (98%) and loss reduction (3.3%). The validation accuracy was 95%, and the validation loss was 0.0888, confirming a good generalization for the new data. Although the performance is better, the addition of CBAM adds to the computational complexity and inference time. How, in this example, the epoch time is slightly faster (24 seconds vs. 20 seconds), which may be due to other optimizations or different hardware. Therefore, more memory and computing resources are required due to the additional layers and operations in CBAM.

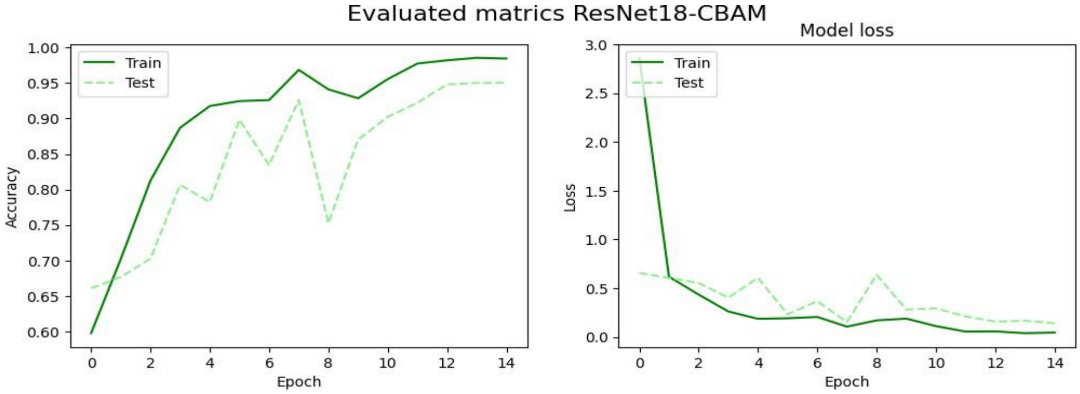


**Figure 3.** Evaluation of ResNet18-CBAM

## 4.2. ResNet18CBAM Deep Performance Metrics

To better understand the performance of the deep learning model with the CBAM-optimized Residual Network 18 (ResNet18) architecture, we will use the obfuscation report and ion classification methods. This model is used in stroke classification tasks through CT scan images of the brain. Both of these methods provide an in-depth view of the model's ability to accurately classify data. The results of this analysis are shown in table 2 and figure 4.

**Table 2.** Classification Report

| Class | Precision | Remember | F1 Score |
|---|---|---|---|
| 0 | 0.96 | 0.96 | 0.96 |
| 1 | 0.94 | 0.93 | 0.93 |
| accuracy | | 0.95 | |
| Macro averaging | 0.95 | 0.95 | 0.95 |
| Weighted average | 0.95 | 0.95 | 0.95 |

In general, both evaluation metrics showed excellent performance of the ResNet18CBAM model in classifying stroke and normal conditions based on brain CT scan age. The confusion matrix in figure 4 shows a high True Positive (TP) value of 300 and a high True Negative (TN) value of 176. This shows that the model can correctly classify stroke and nonstroke images. Meanwhile, a low False Positive (FP) value of 11 and a False Negative (FN) value of 14 which means 14 stroke cases are incorrectly classified as normal. This error has serious clinical implications because it can lead to delays in the treatment of stroke patients.

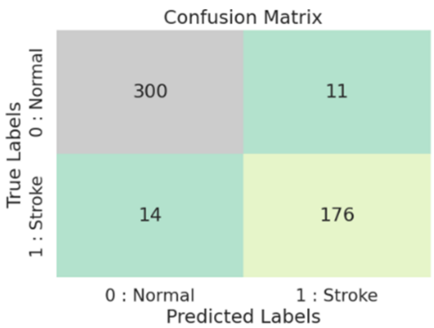


**Figure 4.** Confusion Matrix

On the other hand, the classification report in table 2 displays a high-precision value of 0.96 for the non-stroke class and 0.94 for the stroke class. Recall is also high with a value of 0.96 for non-stroke and 0.93 for stroke. F1score, which is a combination of precision and recall, also scored high at 0.96 for non-stroke and 0.93 for stroke. The overall accuracy of the model is 0.95, which means that 95% of the predictions are correct. Figure 5 shows the ROC curve for all models. AUC, or the area below the ROC curve, measures a model's ability to learn data patterns. AUC values ranged from 0 to 1, where values close to 1 indicated higher learning performance. In this case, the AUC value of the model on the training data is 1.00, while the AUC value on the test data is 0.99. This near-perfect AUC value shows that the model manages to learn patterns in the data very well and is able to distinguish between different classes with good accuracy.

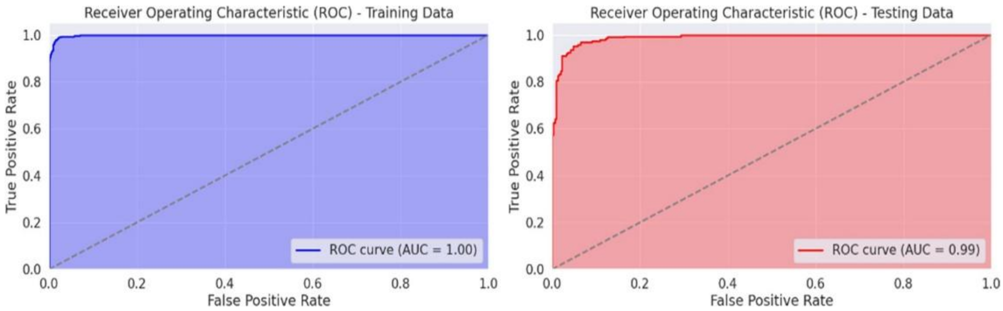


**Figure 5.** ROC-AUC

## 4.3. Model Deployment

The application developed is a web-based system that utilizes the ResNet-CBAM deep learning model. In the implementation process, deep learning models that have been trained using the TensorFlow framework are converted into the model.h5 format to facilitate integration with web-based applications. On the backend side, this application uses the Flask (Python) framework, which allows the management of server logic and communication between the deep learning model and the user interface (frontend). The system is designed to manage the upload of CT scan image files from users and process these images by resizing and normalizing them to match the input format required by the ResNet-CBAM model. Once processed, the system runs the prediction process using the pre-trained model file, model.h5, to detect signs of stroke. Finally, it provides prediction results accompanied by a visualization of the uploaded images, enabling users to interpret the outcomes more effectively.

The prediction process is carried out by integrating the Flask backend with the TensorFlow model, resulting in real-time predictions that can be displayed to users through a web interface. In its main function, the app provides a CT scan image input feature that supports various formats (png, jpg, jpeg, gif). The app ensures that only files with the allowed formats can be uploaded and saves the uploaded images in a specific server directory. The prediction process was carried out by processing the images using the ResNetCBAM model, which has been trained to recognize indicative patterns of stroke in CT scan images. The ResNetCBAM model integrates the attenuation mechanism through the CAM and the Spatial Attention Module (SAM), allowing the model to focus more on the most relevant features and devices in the image. The uploaded image is resized to 224x224 pixels and normalized before being used as a model input. The display for uploading images is shown in figure 6.

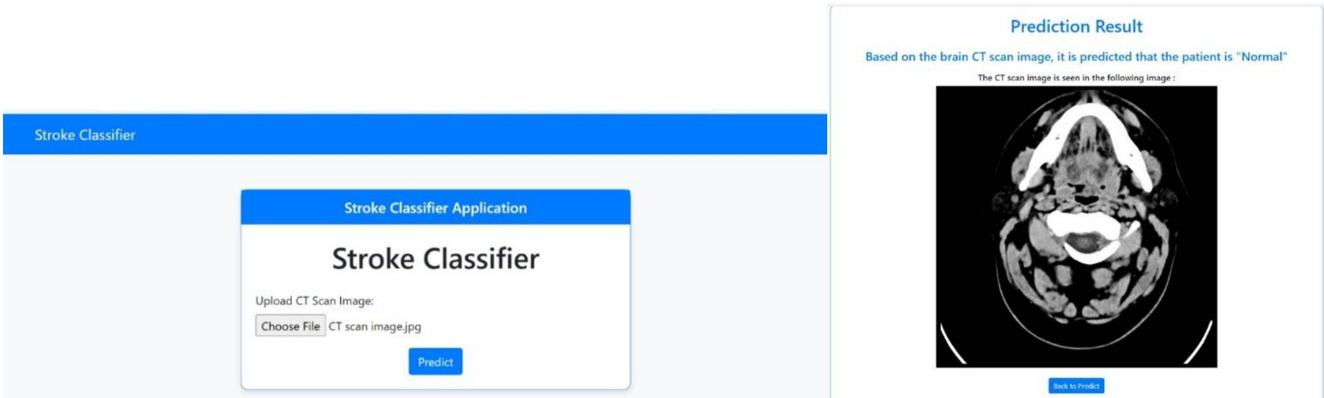


**Figure 6.** Input and Menu Results

A CT scan shows whether or not there are signs of stroke. If the prediction shows a probability of more than 0.5, the application states that the image is most likely to show signs of stroke; Otherwise, the app states that the image is most likely normal. The prediction results are displayed along with the uploaded image, providing visual context that aids in the interpretation of the results. The test of the designed website-based application is carried out using black box testing. The following table 3 shows the testing scheme carried out in this study.

**Table 3.** Black Box Testing Scheme for Stroke Prediction Application

| No | Test Description | Input | Output | Result |
|---|---|---|---|---|
| 1 | Tests whether images in allowed formats can be uploaded | Image files (png, jpg, jpeg, gif) | Images are saved in the specified folder | Successful |
| 2 | Testing whether the uploaded image is displayed directly on the prediction results page | Uploaded CT scan image | Prediction result displayed on the prediction page | Successful |
| 3 | Test whether the prediction result matches the actual label | CT scan image labeled "Stroke" | Prediction result shows "Stroke" information | Successful |
| 4 | Test whether the prediction result matches the actual label | CT scan image labeled "Stroke" | Prediction result shows "Stroke" information | Successful |
| 5 | Test whether the predicted result matches the actual label | CT scan image labeled "Stroke" | Prediction result shows "Stroke" information | Successful |
| 6 | Test whether the predicted result matches the actual label | CT scan image labeled "Stroke" | Prediction result shows "Stroke" information | Failed |
| 7 | Test whether the predicted result matches the actual label | CT scan image labeled "Stroke" | Prediction result shows "Stroke" information | Successful |
| 8 | Test whether the predicted result matches the actual label | CT scan image labeled "Normal" | Prediction result shows "Normal" information | Successful |
| 9 | Test whether the predicted result matches the actual label | CT scan image labeled "Normal" | Prediction result shows "Normal" information | Successful |
| 10 | Test whether the predicted result matches the actual label | CT scan image labeled "Normal" | Prediction result shows "Normal" information | Successful |
| 11 | Test whether the predicted result matches the actual label | CT scan image labeled "Normal" | Prediction result shows "Normal" information | Successful |
| 12 | Test whether the predicted result matches the actual label | CT scan image labeled "Normal" | Prediction result shows "Normal" information | Successful |

## 5. Discussion and Conclusion

This study aims to introduce a stroke classification method based on brain CT scan images using the Convolutional Neural Network approach. The dataset used consisted of 2501 CT scan images of the brain divided into two classes: stroke images (950) and normal images (1551). In building the model, we adopted the CNN architecture, specifically ResNet18, which was then strengthened by the use of the CBAM to improve the model's capabilities. The dataset is divided into two parts: 80% for training and 20% for testing, to ensure the model has good generalizations. In the ResNet18 architecture, CBAM plays a role in using Residual Blocks. The residual block allows the tissue to pass through several other layers, aiding in deeper tissue training without experiencing gradient issues. Thus, the model can extract features from the image and use those features to perform binary classification (stroke or normal) with good accuracy [25]. Various evaluation metrics, such as confusion matrices and other performance metrics, are used to analyze the model's performance in more detail. The results show that the ResNet18 model with CBAM has better performance compared to the standard ResNet18 model. The accuracy of the ResNet18CBAM model reaches 95%, much higher than the accuracy of the standard ResNet18 model which only reaches 64.02%. This suggests that the addition of CBAM to the ResNet18 architecture provides a significant performance improvement in classifying brain CT scan images into stroke or normal.

CBAM's integration with ResNet18 has shown a significant improvement in classification performance, successfully fully achieving an AUC of 0.99 using image input alone. This shows that CNNs can effectively study relevant features directly from the image to a certain degree. In addition, the classification report for the CBAM-optimized ResNet18 model shows outstanding performance. For class 0 (NonStroke), the model achieved a precision of 0.96, in showing that 96% of nonstroke predictions were correct. The drawdown for this class was also 0.96, indicating that the model successfully detected 96% of all actual nonstroke cases. The F1 score for the nonstroke class is 0.96, which is the average of the precision and warning harmonics, confirming the high consistency between the two metrics. With the support of 311 non-stroke cases, this model shows high accuracy and sensitivity in classifying non-stroke cases. For class 1 (Stroke), the precision is 0.94, indicating that 94% of stroke predictions are correct. A drawdown of 0.93 indicates that the model can detect 93% of all actual stroke cases. The F1 score for the punching class is 0.93, which also shows a good balance between precision and alertness. With support for 190 stroke cases, the model also shows strong performance in classifying stroke cases. Overall, the accuracy of this model is 0.95, which means that 95% of all predictions are correct. The results of the confusion matrix show that the model performs well in classifying nonstroke and stroke cases. However, there are mistakes to watch out for, especially in the case of false negatives, where some cases of stroke are incorrectly classified as non-stroke. This suggests that this model has a tendency to miss some stroke cases, potentially affecting patient management and care.

There are several advantages to our research. First, we successfully developed a new deep learning model that combines the CBAM with the ResNet architecture. This integration proves the effectiveness of this innovative approach in the task of classification of stroke ad dressing based on CT images. This method allows the model to effectively highlight and emphasize important features in the CT image that contribute to the diagnosis of stroke, which in turn improves the performance of the classification. Thus, this approach not only allows the model to learn more representative features automatically but also improves the interpretation of the results. The second advantage of this study is the ability of the model to achieve a high level of accuracy in classifying stroke and non-stroke cases. Using the CBAMResNet model, we achieved 95% accuracy, demonstrating that our approach is effective in identifying complex patterns in brain CT images. However, there are also some limitations in our research. First, we acknowledge that the dataset used in this study may have limitations in terms of sample size or resentment of variation in stroke cases. While we strive to ensure diversity in data sets, data shortages or balances between stroke and non-stroke classes can affect model performance and generalizations. Second, although our CBAMResNet model performs well in classifying strokes based on CT images of the brain, we recognize that interpreting the model's results can be challenging.

Although this model shows significant potential in early detection of stroke, there are some limitations that need to be addressed in future research. One of them is the limited size of the dataset, which can affect the diversity of data and the accuracy of the model in dealing with various variations of stroke symptoms. Therefore, the first step that needs to be taken is to increase the size of the dataset by integrating more data from various hospital sources, thus covering a wider variety of patient demographics. Additionally, it is important to address potential biases in the model by applying techniques such as regularization and data augmentation to enrich the variation of the data used in training. Furthermore, to ensure that this model can be implemented practically, further validation with real patient data is required through clinical trials in healthcare facilities. These clinical trials will help evaluate the model's performance in a real-world environment and provide important feedback for further improvement. In addition, exploration of more complex and efficient deep learning architectures can be carried out to improve model performance, especially in overcoming technical challenges and increasing detection speed. Ultimately, the long-term goal is to develop a hardware-based system that can be used for real-time stroke detection in medical facilities, thus enabling faster and more timely diagnosis. Thus, this research not only offers innovative technological solutions, but also paves the way for further development in the field of artificial intelligence-based medical diagnosis.

## 6. Declarations

### 6.1. Author Contributions

Conceptualization: I.T., R.R.I., A.S.P., T.H., E.W., N., A.T., P.L., and R.A.R.; Methodology: T.H.; Software: I.T.; Validation: I.T., T.H., and R.A.R.; Formal Analysis: I.T., T.H., and R.A.R.; Investigation: I.T.; Resources: T.H.; Data

Curation: T.H.; Writing Original Draft Preparation: I.T., T.H., and R.A.R.; Writing Review and Editing: T.H., I.T., and R.A.R.; Visualization: I.T. All authors have read and agreed to the published version of the manuscript.

## 6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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The authors received no financial support for the research, authorship, and/or publication of this article.

## 6.4. Institutional Review Board Statement

Not applicable.

## 6.5. Informed Consent Statement

Not applicable.

## 6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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