



VGGNet-16 Convolutional Neural Network for Classification Of Stroke Based On CT Scan Images

Nur Sakinah ¹, Muh Subhan ¹, Tri Bata Biru Saputri ¹, Tessa Badriah ², Iwan Syarif ²

¹ Informatic Management Study Program, Politeknik Negeri Fakfak, Fakfak, Indonesia

² Department of Information and Computer Engineering, Graduate Program of Engineering,

Politeknik Elektronika Negeri Surabaya, Surabaya, Indonesia

nursakinah@polinef.ac.id, subhan@polinef.id,

batabiru@polinef.id, tessa@pens.ac.id, iwanarif@pens.ac.id

Abstract. Stroke is a blood vessels disease, there is a process of sudden stoppage of blood from damaged blood vessels. Traditionally stroke is classified into two types, namely hemorrhagic rupture of blood vessels and ischemic Causes of strokes include blockages in blood vessels. This research aims to develop software that can automatically predict whether a CT scan image is an ischemic stroke or a hemorrhagic stroke. CT scan image data comes from the Haji Surabaya General Hospital which was taken during the January-May 2019 period and came from 110 patients who had indications of stroke. Before the image data is processed using the Convolutional Neural Network (CNN) algorithm using the VGGNet-16 architecture, the data goes through a preprocessing stage which aims to improve image quality including image conversion, Segmentation to remove skull, and augmentation, Gray scale. The next step is to determine the Convolutional Neural Network (CNN) parameters that will be used to carry out training data to obtain the best classification model. The best parameters in this experiment are Dropout with a value of 0.1, batch size with a value of 15, epoch with a value of 200, Optimizer is Adam, learning rate with a value of 0.0001, Loss function is Binary cross entropy, LR 2 with a value of 0.0001. The experimental results show that the Convolutional Neural Network (CNN) algorithm with the VGGNet-16 architecture produces the highest level of performance where the accuracy value is 99.62% for training data, and 99.5% for testing data.

Keywords: CNN; VGG; Stroke; Classification; CT Scan Image.

1 Introduction

Stroke is a blood vessels disease, there is a process of sudden stoppage of blood from damaged blood vessels. Traditionally stroke is classified into two types, namely hemorrhagic rupture of blood vessels and ischemic Causes of strokes include blockages in blood vessels [1]. The treatment and diagnosis of stroke is done by clinical examination, followed by radiology modalities such as Computed tomography (CT) scan. CT scan based imaging is the most commonly used imaging modality to detect stroke [2]. CT scan is one of the neuroimaging techniques that has become an integral approach and has a very important role for stroke detection, characterization, and prognosis of patients experiencing stroke symptoms [3]. Diagnosis and classification of diseases are widely developed with computer aided

© The Author(s) 2024

M. U. H. Al Rasyid and M. R. Mufid (eds.), *Proceedings of the International Conference on Applied Science and Technology on Engineering Science 2023 (ICAST-ES 2023)*, Advances in Engineering Research 230,

https://doi.org/10.2991/978-94-6463-364-1_104

diagnostic methods, using deep learning approaches. Deep learning, derived from artificial neural networks, mimics human brain intelligence in increasingly sophisticated and independent ways [4].

Convolutional Neural Network (CNN) is a deep learning method consisting of several layers for two-dimensional data classification in object identification with system performance that is considered to have a deep learning level. Research related to CNN approaches specifically for detection and classification is widely used, including stroke detection using CNN with OzNet Architecture achieving an accuracy value of 98.42% [5]. Some studies that show CNN with VGGNet Architecture getting high accuracy performance include Brain Tumor Identification Research, with a fairly high accuracy value performance 90.37% [6]. In addition, pneumonia classification research with imbalance data by performing an augmentation process shows a high accuracy 92% [7]. Another study that uses the VGGNet architecture, namely Glioma Classification, shows perfect accuracy performance of 100% [8]. In addition to being used for disease classification, other objects such as fish show good results such as Freshness of Red Snapper Classification Research using VGGNet architecture achieved a value of 98.40% [9], other fish classification namely classifying milkfish's freshness on eye images CNN VGGNet architecture obtained the highest accuracy value compared to other architectures which is 98.40% [10].

Based on some of the research above, this study aims to develop software that can classify or predict CT scan images of stroke patients automatically CT scan images of ischemic stroke or hemorrhagic stroke patients, using the Convolutional Neural Network approach with VGGNet-16 architecture.

2 Methodology

2.1. Convolutional Neural Network (*Cnn*)

CNN is a variation of Multilayer Perceptron that is inspired by human neural networks and belongs to the Deep Neural Network type due to its high network depth. CNN is designed to process two-dimensional data that is often applied to object image classification. The general architecture of CNN can be seen in Fig.1. CNN architecture has two main parts, Feature Learning and Classification. Feature learning consists of convolution layer, activation function, and pooling. These layers are often arranged in several layers according to the needs of the architecture. The classification part consists of Flatten, Fully Connected and activation function. The convolutional layer will detect features in the form of edges in the image, then the subsampling layer will reduce the dimensions of the features obtained from the convolutional layer, finally forwarding to the output node through the forward propagation process. Fully connected layer functions to combine feature extraction into classes using Softmax activation to get class output results [11][12][13].

2.2. VGGNet-16 Architecture

VGGNet-16 architecture can be seen in Fig. 2. VGGNet-16 has 13 convolution layers 5 pooling layers and 3 fully connected layers. VGG16 uses the concept of blocks to form convolution layers, each convolution layer has a size of 3 x 3 and stride 1. At the

end of the block, a pooling layer with size 2 x 2 and stride 2 is used. The pooling layer uses MaxPooling, but not all convolution layers have a pooling layer. All hidden layers are equipped with ReLU layers. After the first and second layers are fully connected, dropout technology is also used to prevent network overfitting [14].

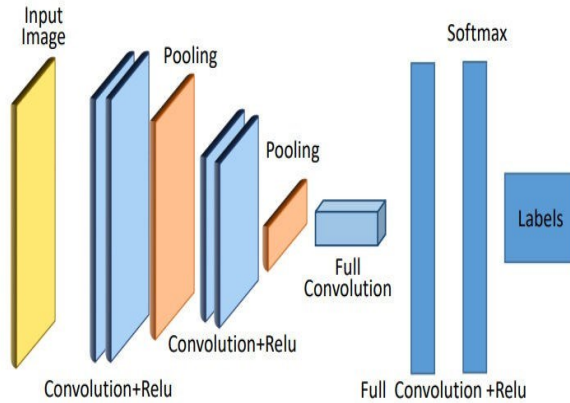


Fig..1. Convolutional Neural Network with [13].

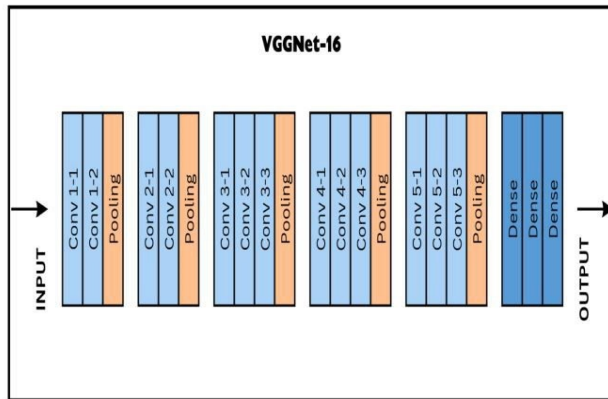


Fig.2. VGGNet-16 Architecture with CNN.

3 The Proposed System

Generally, the steps to develop a classification system consist of image data collection, image preprocessing, parameter initialization, data training using VGGNet-16 Architecture in CNN method, and data testing. In the system built, the dataset is processed first with several processes such as CT to jpg data conversion, segmentation to remove skulls, augmentation and Gray scale for images. Parameter initialization, then training on image data made according to the parameters that have been determined. Furthermore, testing is carried out from the model that has been obtained from the training process using test data. The process will continue to repeat to the model with the best accuracy.

3.1. Data Collection

The Data Collection used in this study is a CT scan dataset of the patient's brain consisting of Ischemic Stroke image data and Hemorrhagic Stroke image data. The dataset was obtained from the Hajj Hospital in Surabaya, Indonesia. The data obtained amounted to 110 patients, with ages varying between 11-85 years old who were female and male in the period January to May 2019. The distribution of ischemic patient data was 99 patients and data for 11 Hemorrhagic patients. The data obtained is still very minimal to be processed using the CNN approach, because CNN will produce good performance with large data sets. So that the data obtained must go through image preprocessing to get more data and ready to be processed into CNN.

3.2. Preprocessing Image data

Image data preprocessing carried out in this study includes 4 stages, namely conversion, segmentation to remove skull, augmentation and image grayscale.

1) Conversion,

The data obtained is still in the form of dicom extension. The data is converted using syngo fastview software which is radiology imaging software.

2) Segmentation to remove skull

The segmentation stage uses a bilateral filter which is defined as a weighted average of pixels that takes into account variations in intensity to serve to refine the image to maintain the edges of adjacent pixel values [15] then applies the threshold method with a threshold value of 200 where images that have a color intensity of more than 200 will be removed, namely in the part of the skull that has a high color density. In the picture can be seen the results of skull removal. The segmentation stages can be seen in Fig. 3.

3) Augmentation

Augmentation Process to expand the training data set. Considering that CNN has many parameters, it requires many image variations for the training process in the algorithm. This is done because the data set is less and the hemorrhagic image data is not balanced with ischemic. Augmentation implementation is done using the Keras deep learning library through the Image Data Generator there are 5 methods used in augmentation techniques. The general affine transformation method used in augmentation techniques is random brightness, horizontal flip, vertical flip and random rotation, zoom in image [15] Each technique adds 100 data After augmentation the data used in each type of stroke has a different amount, there is 500 image data for hemorrhage stroke and 500 data for ischemic stroke.

4) Greyscale

This stage is a process to scale the gray scale image. The CT scan image from data collection has a digital image value that has a pixel range value between 0-255 which describes the gray scale color. while the image of preprocessing results such as conversion, segmentation and augmentation still represents RGB color. so that the preprocessed image will be processed into a Gray scale image. Gray scale process will be carried out using black as the minimum color represented by 0 and white as the maximum color represented by 1.

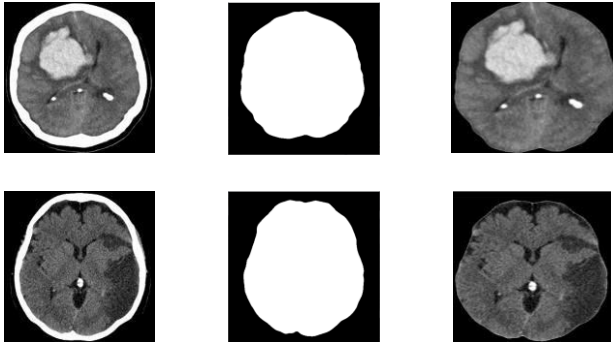


Fig.3. Segmentation to remove skull

3.3. Parameters Inisialization

After the dataset making preprocessing, then determines the initialization of the parameters needed, Parameters are variables that determine how a model is trained. In this experiment, the researcher also set the Convolutional Neural Network (CNN) parameters and made parameter adjustments during the experiment. The parameter inisialization can be seen on table 1.

3.4. Training Data

Data training is carried out to obtain the best classification model based on predetermined parameter initialization. Model training aims to enable the system to recognize objects and classify them according to their respective classes. VGGNet-16 is the CNN architecture used in this research. The VGGNet-16 model consists of 16 CNN layers consisting of 13 convolutional layers, 3 fully connected layers, and 1 softmax. The model generated in the data training process will be used as new testing data to be classified into 2 label classes, namely ischemic and hemorrhagic. The design of this research system adds zero padding, L2R parameters in the first layer of convolution and batch normalization after each convolution process which is useful for reducing missing information data and normalizing the flow axis. The activation function used in the fully connected layer is flatten which serves to perform data structuring, dropout serves to limit incoming neurons, L2R is a method applied to a model to avoid overfitting and softmax is an activation function to calculate the probability of training data on objects consisting of 2 classes. CNN VGGNet-16 architecture for Training data can be seen in table 2.

3.5. Testing Data

The best model in the data training process will be the model for testing new data that has not been used in the training process. To evaluate the performance of the algorithm, confusion matrix values are needed which can be seen in table 3. The metrics score used to evaluate the VGGnet-16 architecture is a performance measurement method using accuracy parameter.

Table 1. Parameters CNN.

Parameters	Value
Dropout	0.1
Optimizer	ADAM
Learning rate	0.0001
Loss function	Binary cross entropy
Epoch	50,60,70,80,90,100
Batch size	15, 25, 32
LR 2	0,0001

Table 2. Network Layer Cnn Vggnet-16 Architecture.

Layer Type	Feature maps	Kernel size	Size	Activation Function
Image (input)	3	-	50 x 50	-
Convolution	64	3x3	50 x 50	Relu
Convolution	64	3x3	50 x 50	Relu
Max Pooling	64	2x2	25 x 25	Relu
Convolution	128	3x3	25 x 25	Relu
Convolution	128	3x3	25 x 25	Relu
Max Pooling	128	2x2	12 x 12	Relu
Convolution	256	3x3	12 x 12	Relu
Convolution	256	3x3	12 x 12	Relu
Convolution	256	3x3	12 x 12	Relu
Max Pooling	256	2x2	6 x 6	Relu
Convolution	512	3x3	6 x 6	Relu
Convolution	512	3x3	6 x 6	Relu
Convolution	512	3x3	6 x 6	Relu
Max Pooling	512	2x2	3 x 3	Relu
Convolution	512	3x3	3 x 3	Relu
Convolution	512	3x3	3 x 3	Relu
Convolution	512	3x3	3 x 3	Relu
Max Pooling	512	2x2	1 x 1	Relu
Fully Connected			4096	Relu
Fully Connected			4096	Relu
Fully Connected			1000	Relu
output			2	SoftMax

Table 3. Performance Confusion Matrix.

	Prediction Labels	
	Positive	Negative

Labels	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

4 Experiment And Result

CNN performs better with large data sets. So in determining training data and testing data using augmentation techniques, the data used for the training process uses 1000 datasets through the augmentation process of 500 ischemic image data and 500 hemorrhagic image data. The holdout method is applied to all experiments using 80% train set and 20% test set. New data testing process based on the best model is tested using 1000 new data consisting of 500 ischemic data and 500 hemorrhagic data.

4.1. Performance Analysis Of The Vggnet-16 Architecture

1) Training Data

Data training process to get the best classification model was carried out by conducting 3 experiments based on CNN parameters that have been determined at the beginning by doing 3 different batch size initializations, namely 15, 25 and 32. The following are the results of the experiments that have been carried out:

a) First Experiment

The 1st experiment can be seen in table 4, the experiment using parameters with Batch size 15 with epoch experiments 50, 60, 70, 80, 90, 100 and 200. The performance results show that the highest accuracy is on epoch 200 with an accuracy value 99.62%.

b) Second Experiment

The 2nd experiment can be seen in table 5, the experiment using parameters with Batch size 25 with epochs 50, 60, 70, 80, 90, 100 and 200. The performance results show that the highest accuracy is on epoch 100 with an accuracy value 98.90%.

c) Third experiment

The 3rd experiment can be seen in table 6, the third experiment using parameters with Batch size 32 with trial epochs 50, 60, 70, 80, 90, 100 and 200. The performance results show that the highest accuracy is found at epoch 100 with an accuracy value 99.40%.

Based on the experiments that have been carried out, it can be seen that there is the best accuracy value in each experiment with a relatively high value above 98%. The best performance results can be seen in table 7 in the 1st experiment at the 200th iteration with an accuracy value of 99.60%. The best parameters in this experiment are batch size with a value of 15, epoch with a value of 200, Dropout with a value of

0.1, Optimizer is Adam, learning rate with a value of 0.0001, Loss function is Binary cross entropy, LR 2 with a value of 0.0001. So that this model will be used as new testing data.

Table 4. Result First Experiment.

Epoch	Val Loss	Val Acc	Loss	Accuracy
50	0.4882	0.96	0.5547	0.9334
60	0.6217	0.88	0.4932	0.9623
70	0.4832	0.96	0.5002	0.9484
80	0.774	0.87	0.4393	0.9799
90	0.4225	0.985	0.4619	0.9748
100	0.5299	0.91	0.4573	0.9685
200	0.4174	0.975	0.3344	0.9962

Table 5. Result Second Experiment.

Epoch	Val Loss	Val Acc	Loss	Accuracy
50	2.007	0.965	1.998	0.966
60	1.978	0.965	1.978	0.970
70	1.916	0.985	1.950	0.974
80	1.921	0.985	1.949	0.969
90	0.960	0.960	0.976	1.952
100	1.892	0.970	1.860	0.989
200	1.633	0.825	1.633	0.980

Table 6. Result Third Experiment.

Epoch	Val Loss	Val Acc	Loss	Accuracy
50	0.547	0.945	0.531	0.956
60	0.472	0.890	0.472	0.963
70	0.446	0.965	0.443	0.974
80	0.729	0.885	0.500	0.964
90	0.481	0.965	0.431	0.981
100	0.511	0.935	0.432	0.978
200	0.472	0.980	0.376	0.994

Table 7. Result Third Experiment.

Epoch	ValLoss	ValAcc	Loss	Accuracy	Batch Size
200	0.417	0.975	0.334	0.996	15
100	1.892	0.970	1.860	0.989	25
200	0.472	0.980	0.376	0.994	32

2) Graphics Training Data

The following is a figure of graphic of the training model with the best value namely graphic of Accuracy can be seen in Fig. 4. graphic of train-test loss can be seen in Fig. 5. , while the Graphics Test Loss and Accuracy can be seen in Fig.6., then Graphics Train Loss and Accuracy can be seen in Fig.7.

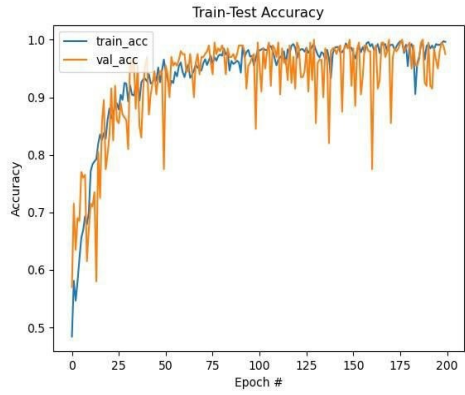


Fig. 4. Graphics Train-Test Accuracy.

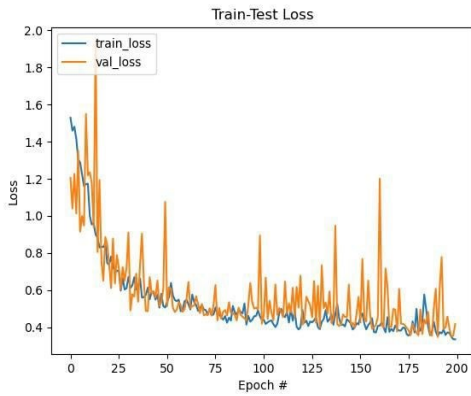


Fig. 5. Graphics Train-Test Loss

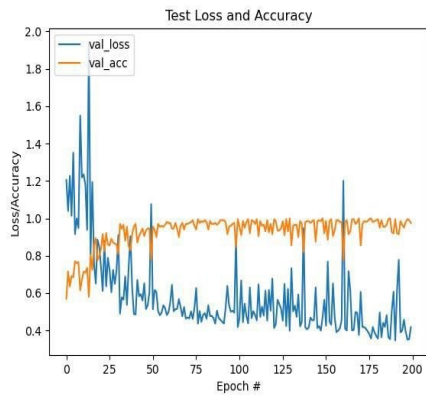


Fig. 6. Graphics Test Loss and Accuracy.

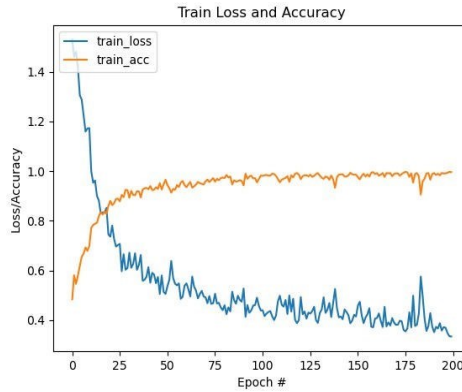


Fig. 7. Graphics Train Loss and Accuracy.

3) *Testing Data*

The data training process produces a classification model, the classification model with the best value is used in the testing data stage using new data for the classification of stroke diseases. testing data there are 500 ischemic image data and 500 hemorrhagic image data. The new data classification results can be seen in table 8 as follows

Table 7. Result Testing New Data.

Ischemic Image Data (1) : 500	
Hemorrhagic Image Data (0) : 500	
Total Misclassification of each class	Classification Results:
1. Ischemic in images 11, 88, 99	1. True Positive: 497
2. Hemorrhagic in images 300, 349	2. False negative: 3
	3. True Negative: 498
	4. False positive: 2

Data testing of this data modeling shows that there are 5 data tested out of 1000 total data that have not been represented in the data modeling so that the success rate obtained is 99.5% accuracy. The Model Data showed excellent results. The classification software used to test the new data can be seen in Fig. 8, by opening the latest stroke patient image then do the classification, the results can be seen in Fig.9 by showing the results of stroke classification along with the classification probability value.

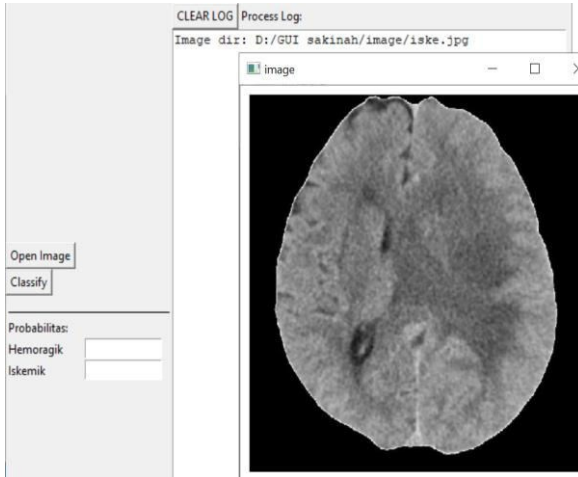


Fig. 8. Software classification.

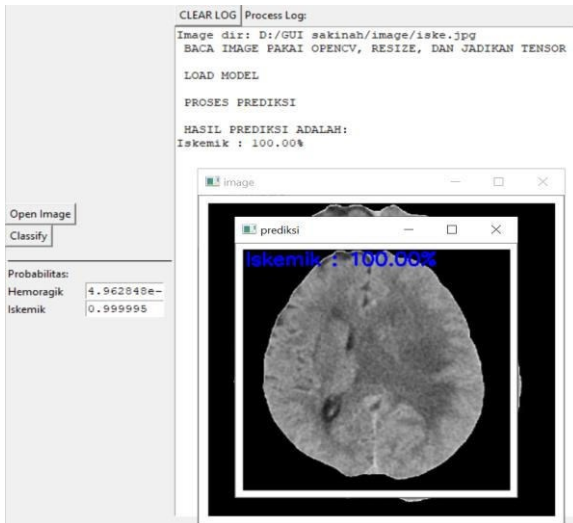


Fig. 9. Result Classification using Software.

5 Conclusion

This study classifies stroke diseases using the CNN model with VGGNet-16 Architecture carried out for ischemic and hemorrhagic stroke base on CT Scan. classification with 3 different experiments based on CNN parameter initialization. The best parameters in this experiment are batchsize with a value of 15, epoch with a value of 200, Dropout with a value of 0.1, Optimizer is Adam, Learning rate with a value of 0.0001, Loss function is Binary cross entropy, LR 2 with a value of 0.0001.

The results of training data achieve 99.62% and testing new data achieve 99.5%. based on the percentage of training data and testing data shows very good results. However, it is necessary to add data continuously, considering that the data used in this study is only limited, such as hemorrhagic stroke image data, so it is necessary to expand the data as learning data. The VGGNet-16 architecture is also very suitable for image data classification. However, differences in network architecture and parameters such as the number of epochs, batch size, and learning rate used can also affect the results of the CNN model. for future development, this software will be equipped with a parameter optimization feature to obtain a combination of the values of the learning rate and the number of epochs. parameter optimization feature to get the best combination of parameters for the CNN algorithm so that it can produce optimal performance.

Acknowledgment

The PPPM of Politeknik Negeri Fakfak support part of funded this study. Researchers are appreciative of this help. The researchers would also like to thank the Surabaya Hajj Hospital for supplying the data. In addition, we would like to convey our gratitude to all of our direct and indirect supporters.

References

- 1 Chang JC. Stroke Classification.: Critical Role of Unusually Large von Willebrand Factor Multimers and Tissue Factor on Clinical Phenotypes Based on Novel "Two-Path Unifying Theory" of Hemostasis. *Clin Appl Thromb Hemost*. Januari 2020.
- 2 CHIN C. L.: DKK. 2017. An automated early ischemic stroke detection system using CNN deep learning algorithm. 2017 IEEE 8th International Conference on Awareness Science and Technology (iCAST), pp.368-372. doi:10.1109/ICAwST.2017.8256481
- 3 M. Abdalkader, J. E. Siegler, J. S. Lee, S Yaghi, Z. Qiu, X. Huo, Z. Miao, B. C.V. Campbell, T. N.: Nguyen "Neuroimaging of Acute Ischemic Stroke: Multimodal Imaging Approach for Acute Endovascular Therapy *J Stroke*". vol. 25, pp.55-71. January 2023.
- 4 L. Cui, Z. Fan , Y Yang, R Liu, D Wang, Feng Y, Lu J, Fan Y.: "Deep Learning in Ischemic Stroke Imaging Analysis: A Comprehensive O. Ozaltin, O. Coskun , O.Yeniay 1 and A. Subasi. "A Deep Learning Approach for Detecting Stroke from Brain CT Images Using OzNet". *Bioengineering* .Vol.9.pp789 , 2022.
- 5 S. Aulia, D. Rahmat.: "Brain Tumor Identification Based on VGG-16 Architecture and CLAHE Method", vol.6, March 2022.
- 6 M. Idhom, D. A. Prasetya, P. A. Riyantoko, T. M. Fahrudin,A. P. Sari.: "Pneumonia Classification Utilizing VGG-16 Architecture and Convolutional Neural Network Algorithm for Imbalanced Datasets" Vol.4, pp. 73-82, , June 2023.
- 7 E. Minarno, B. Y. Sasongko, Y. Munarko, H. A. Nugroho, Z. Ibrahim .: "Convolutional Neural Network featuring VGG-16 Model for Glioma Classification," *JOIV Int. J. Inform. Visualization*, vol.2(3), September 2022.
- 8 M. Subhan, N. Sakinah.: "Classification Freshness of Red Snapper (*Lutjanus Campechanus*) Based on Eye Image Using Convolutional Neural Network", *EPI International Journal of Engineering* vol.5, February 2022.

- 9 E. Prasetyo, R. Purbaningtyas, R. D. Adityo , E. T. Prabowo, A. I. Ferdiansyah.: “A Comparison Of Convolution Neural Network For Classifying Milkfish’s Freshness On Eye Images” *JTIK*. Vol. 8, pp. 601-608 Juni 2021.
- 10 N. F. Nissa, A. Janiati, N. Cahya, Anton, P. Astuti.: ”Neural Network (CNN) Method for Women’s Skin Classification”. *Scientific Journal of Informatics*, Vol. 8, No. 1, pp 143-153, May 2021.
- 11 I. A. Anjani, Y. R. Pratiwi, and N. B. Nurhuda.: "Implementation of Deep Learning Using Convolutional Neural Network Algorithm for Classification Rose Flower". *International Conference on Science Education and Technology (ICOSETH)*. 2021
- 12 Afridi, Tariq & Alam, Aftab & Khan, Numan & Khan, Jawad.: “A Multimodal Memes Classification: A Survey and Open Research Issues”. September 2020.
- 13 Yulin Li.: “Face age and gender recognition based on improved VGGNet algorithm”, *Journal of Information and Computing Science*. England UK 2019.
- 14 T. Badriyah, N. Sakinah, I. Syarif, D.R Syarif.: “Segmentation Stroke Objects based on CT Scan Image using Thresholding Method”. *2019 First International Conference on Smart Technology & Urban Development (STUD)*, pp.1-6, Desember 2019.
- 15 N. Sakinah, T. Badriah, I.Syarif.: “Performance Analysis Machine Learning Algorithms For Classification Of Stroke Using Ct Scan Images” Vol.7, pp.833-844. *JTIK* 2020.
- 16 T. Badriyah, D. Santoso, I. Syarif, D. Syarif.: (2019). “Improving stroke diagnosis accuracy using hyperparameter optimized deep learning”. vol. 5, pp.256-272. *IJAIN 2019*.

Open Access This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (<http://creativecommons.org/licenses/by-nc/4.0/>), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

