A New Method for Classifying Intracerebral Hemorrhage (ICH) Based on Diffusion Weighted – Magnetic Resonance Imaging (DW-MRI)

Andi Kurniawan Nugroho, Jajang Edi Priyanto, Dinar Mutiara Kusumo Nugraheni
Electrical Engineering Department, Universitas Semarang, Semarang, Indonesia
Public Health Department, Institut Kesehatan Indonesia, Jakarta, Indonesia
Informatic Department-Faculty of Science and Mathematics, Universitas Diponegoro, Semarang, Indonesia

***Abstract*—Stroke is a condition where the blood supply to the brain is cut off. This occurs due to the rupture of blood vessels in the intracerebral area or Intracerebral Hemorrhage (ICH). Examination by health workers is generally carried out to get an overview of the part of the brain of a patient who has had a stroke. The weakness in diagnosing this disease is that deeper knowledge is needed to classify the type of stroke, especially ICH. This study aims to use the Modified Layers Convolutional Neural Network (ML-CNN) method to classify ICH stroke images based on Diffusion-Weighted (DW) MRI. The data used in this study is a DWI stroke MRI image dataset of 3,484 images. The data consists of 1,742 normal and ICH images validated by a radiologist. Because the data used is relatively small and takes into account the computational time, Stochastic Gradient Descent (SGD) is used. This study compares the basic CNN model scenario with the addition of layers to the original CNN model to produce the highest accuracy value. Furthermore, each model is cross-validated with a different k to produce performance in each model as well as changes to batch size and epoch and comparison with machine learning models such as SVM, Random Forest, Extra Trees, and kNN. The results showed that the smaller the number of batch sizes, the higher the accuracy value and the number of epochs, the higher the number of epochs, the higher the accuracy value of 99.86%. Then, four machine learning methods with accuracy, sensitivity, and specificity below 90% are all compared to CNN2. As a summary of this research, the proposed CNN modification works better than the four machine learning models in classifying stroke images.**

***Keywords*—Batch size; Epoch; ML-CNN; SGD;Stroke**

I. INTRODUCTION

There are more than 3.4 million new intracerebral hemorrhages each year. Globally, more than 28% of all stroke events are intracerebral hemorrhage. Annually, more than 23% of all intracerebral hemorrhages occur in persons aged 15-49 years [1]. Stroke is a fairly serious problem because stroke is a medical emergency that can threaten disability and death in patients if it is not handled quickly and appropriately. In the diagnosis of stroke, neurological imaging always plays an important role. Most stroke patients carry out examinations using Computerized Tomography Scanning (CT scan) radiology modalities. However, the CT scan image results for each patient vary according to the time interval that has passed since the stroke. Therefore, a radiologist plays a major role in determining the management of stroke patients whether further imaging is carried out using Magnetic Resonance Imaging (MRI) to find out how severe the cell damage is in the brain, so that knowledge of the patient's radiological image will determine the treatment to be undertaken by the patient [2].

Stroke causes a reduction or stoppage of blood flow carrying oxygen which results in the death of brain cells. Based on the cause, stroke is divided into two, namely ischemic stroke where the blood supply stops flowing to the brain due to a blockage and hemorrhagic stroke where bleeding occurs in the brain tissue [3]. It is important to receive the correct diagnosis before stroke treatment begins, because treatment for stroke differs according to the type of stroke. If the patient fails to receive prompt and appropriate treatment, a stroke will have serious consequences and cause permanent damage to the brain and even death to the patient. Treatment and diagnosis of stroke is carried out by clinical examination, and then followed by examining radiologist modalities such as CT scan and MRI [4].

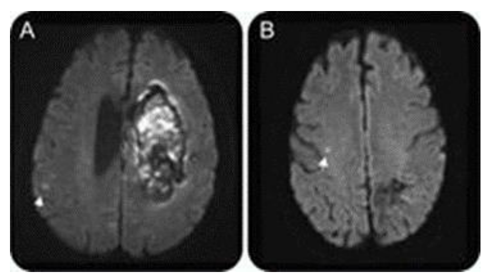


Fig. 1. DWI lesions in the acute and nonacute time periods.

Fig. 1 shown A visible parietal DWI lesion one day after a contralateral basal ganglia hemorrhage in a 66-year-old man (A) and a frontal DWI lesion two years after a contralateral parietal bleeding in a 69-year-old man (B). DWI = diffusion weighted imaging. Computational analysis of MRI images often aids physicians in diagnosis and helps reduce the subjectivity of diagnosis, and also provides higher accuracy for intensive care. Modern applications of artificial intelligence are designed to help humans solve various problems. CNN is a subcategory of deep learning development that is now widely used in neuroimaging [5]. Deep learning techniques and the use of CNN are often used to diagnose acute ischemic stroke. A popular topic in automated diagnostics is end-to-end system architecture. In this study, several CNN modifications are proposed to find the best performance value in classifying ICH stroke and normal conditions so that doctors can quickly make the quickest diagnosis to determine the therapy given. This paper consists of five sections: the Section I contains an introduction; Section II contains related work; Section III contains the methodology used in the research; Section IV contains performance results from three CNN models, hyperparameters, and comparisons with machine learning models; and Section V contains conclusions and future research work.

II. Related Work

Recently, several important publications have presented implemented algorithms classifying brain stroke. In addition, the ischemic stroke lesion segmentation method and risk prediction are also applicable to stroke diagnosis [6]. Several studies have used common deep learning models such as Inception-V3 and EfficienNet-b0 to detect acute stroke using DW-MRI with an accuracy value of 86.3% [7]. A study related to the diagnosis and prediction of stroke by developing a detection system for only one type of stroke have detected early ischemia automatically using the Convolutional Neural Network (CNN) algorithm with 256 original images and augmented images, with the classification results obtaining an accuracy value of 90% [8]. Another study used the CNN algorithm with an open stroke dataset from www.radiopaedia.org to classify patient data into three classes, namely normal, ischemic stroke, and hemorrhagic stroke through CT scan images.

Meanwhile, other researchers using the same dataset performed hyperparameter optimization in the Deep Learning algorithm to improve the accuracy of stroke diagnosis using CT scan image segmentation with the thresholding method and the binarization process. The implementation of the threshold method uses global binary thresholding and Otsu thresholding [9].

I.P. Kerta et al. [10] have segmented patient data to produce patient class labels and classify the results of grouping data to test the performance of the classification algorithm used. A total of 4,906 patient data used in this study were grouped using the K-Means method into several clusters, including two clusters, three clusters, four clusters, and five clusters, and the findings of these data groupings will be classified. The classification results produce the best accuracy value on the number of clusters tested, namely two clusters of 99.71%.

Jenna and Kumar [11] have performed a stroke classification using International Stroke trial data. The database includes patient information, patient history, hospital details, risk factors, and symptoms. Preprocessing is done to eliminate missing and inconsistent data. After preprocessing, 350 samples were taken in this work, with parameters sensitivity, specificity, accuracy, precision and F1 scores calculated to evaluate the performance of various kernel functions of the SVM classifier. The experimental results obtained the best precision in the kernel linear function with an accuracy value of 91%.

P. Govindarajan et al [12] presented a prototype for classifying strokes that combines text mining and machine learning algorithms. At the data collection stage, patient data from 507 patients were collected from Sugam Multispecialty Hospital, Kumbakonam, Tamil Nadu, India. Processed data is fed into various machine learning algorithms such as artificial neural networks, Support Vector Machine (SVM), and random forest. Among these algorithms, the neural network trained with the Stochastic Gradient Descent algorithm outperforms other algorithms with a higher classification accuracy of 95%.

Y. Q. Zhang et al investigated the ability of a machine learning model based on MRI radiomic features (ML) to classify time since stroke onset (TSS), which could aid in stroke assessment and treatment options. This study involved 84 patients with acute ischemic stroke. Segmentation of the infarct area is made manually with 3D-slicer software. A total of 4312 radiomic features from each image sequence were captured and used in six machine learning models to estimate stroke onset time for binary classification ($\leq$ 4.5 hours). Receiver-Operating Characteristic (ROC) curves and other parameters are calculated to evaluate the performance of the model in the training and test groups. Twelve radiomic results and six clinical features were selected to construct the ML model for TSS classification. The deep learning model-based DWI/ADC radiomic feature showed the best for binary TSS classification in the independent test group, with AUC 0.754, accuracy 0.788, sensitivity 0.952, specificity 0.500, positive predictive value 0.769, and negative predictive value 0.857, respectively [13].

Our contributions to this study are as follows:

1) We propose a classification of stroke intracerebral hemorrhage (ICH) using MRI images with modifications to the addition of a convolution layer to the simple CNN model with hyperparameter tuning, such as changes in epoch, batch size, and the use of k- fold validation in knowing performance values from a limited number of datasets.

2) We have compared the performance of Modified Layer CNN (ML-CNN) with machine learning models to produce a good method for classifying DW- MRI ICH stroke images with normal images.

Several CNN models were analyzed using several optimal methods to compare the performance of various machine learning algorithm approaches using four parameters, namely accuracy, precision, recall, f1- measure, and k-fold cross-validation to optimize performance, resulting in high prediction accuracy.

III. Methodology

A. Data Collection

The stages of data collection in this study were to collect image data from DW-MRI of the patient's brain consisting of Intracerebral Hemorrhage (ICH) stroke image data and normal image data. DW-MRI image data comes from Gatot Subroto Hospital Jakarta which was taken during the January-May 2019 period and came from 430 patients with ICH stroke indications. The image taken has a slice thickness of 5.0 mm, the distance between slices is 6.5 mm, the pixel spacing is 0.7 mm and the original image size is 320 pixels x 320 pixels.

The data that has been collected is labeled to distinguish between ICH stroke data and normal data by radiologists. To eliminate noise, a filter is performed and to add data to prevent overfitting, augmentation is carried out in real time. Images were entered for each CNN model and the values for accuracy, precision, recall, f1-score, and specificity were calculated. Next, the collected data is compared with machine learning models to find out how high the performance of each of these models is. The research method is shown in Fig. 2.

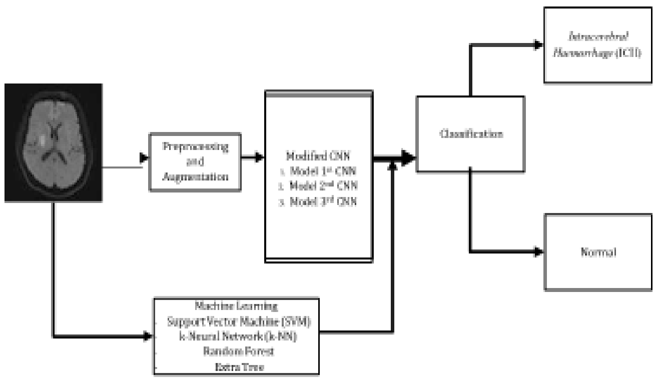


Fig. 2. Research method.

B. CNN Models

This research was conducted using three variations of the CNN architecture to obtain the most appropriate architecture in detecting and differentiating the presence of intracerebral hemorrhage (ICH) stroke and normal brain images. Computations are performed using NVIDIA GeForce GTX 1650 GPU RAM 16 GB 2600 MHz DDR4 to shorten the compilation time of the CNN program.

The architectural design is presented in Table I. Fig. 3 shows the basic architecture of the CNN method (CNN1). Fig. 4 (CNN2) shows an additional development of the convolution layer from CNN1. Fig. 5 (CNN3) is the development of the CNN2 model by adding each layer and its activation function to get the classification accuracy value. Comparisons can be made between these designs individually (CNN1, CNN2, CNN3) or between design groups to obtain the most appropriate type of design in classifying DW-MRI image data.

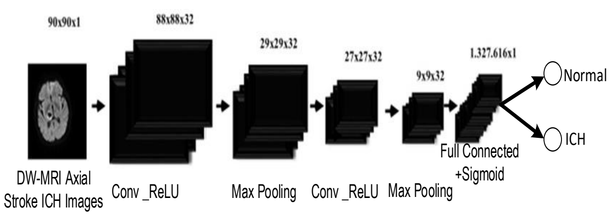


Fig. 3. CNN1 architecture visualization.

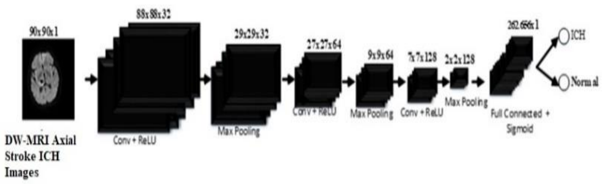


Fig. 4. CNN2 architecture visualization.

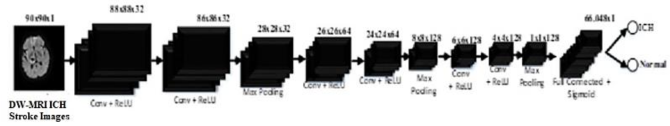


Fig. 5. CNN3 architecture visualization.

TABLE I. CNN CONFIGURATION TESTED

CNN1	CNN2	CNN3
Input Layer = 90x90x1	Input Layer = 90x90x1	Input Layer = 90x90x1
Conv. Layer (layer contains 32 filter of [3 3])	Conv. Layer (layer contains 32 filter of [3 3])	Conv. Layer (layer contains 32 filter of [3 3])
ReLU	ReLU	Conv. Layer (layer contains 32 filter of [3 3])
MaxPOOL (3x3, with stride [1 1])	MaxPOOL (3x3, with stride [1 1])	ReLU
Conv. Layer (layer contains 32 filter of [3 3])	Conv. Layer (layer contains 64 filter of [3 3])	MaxPOOL (3x3, with stride [1 1])
ReLU	ReLU	Conv. Layer (layer contains 64 filter of [3 3])
MaxPOOL (3x3, with stride [1 1])	MaxPOOL (3x3, with stride [1 1])	Conv. Layer (layer contains 64 filter of [3 3])
Dropout Layer (drop probability = 0.5)	Conv. Layer (layer contains 128 filter of [3 3])	ReLU
Full Connected Layer	ReLU	MaxPOOL (3x3, with stride [1 1])
Sigmoid Layer	MaxPOOL (3x3, with stride [1 1])	Conv. Layer (layer contains 128 filter of [3 3])
Classification Layer	Dropout Layer (drop probability = 0.5)	Conv. Layer (layer contains 128 filter of [3 3])
	Full Connected Layer	ReLU
	Sigmoid Layer	MaxPOOL (3x3, with stride [1 1])
	Classification Layer	Dropout Layer (drop probability = 0.5)
		Full Connected Layer
		Sigmoid Layer
		Classification Layer

C. Augmentation Data

Data Augmentation is a technique to increase the diversity of image data by performing basic transformations such as rotation, shared, horizontal flip, and zoom. According to Luis Perez et al. [14] by using this technique, the model can overcome the problem of overfitting and improve the accuracy of the CNN model. In this study, each class (ICH and Normal) used 430 data with 4 (four) geometric transformations, and generated data for each class of 1720 datasets per class. In each epoch, the model receives images with different transformations. This study applies real time data augmentation [15].

Configuration of data augmentation in this study is in the form of:

1) Shared range = 20 skews the image to a maximum angle of 20 degrees. The value used should not be too large because it will make the image flat.

2) Rotation range = 20 randomly rotates the image up to a maximum angle of 20 degrees.

3) Horizontal flip = True flips the image horizontally.

4) Zoom range = [0.75-1.0] randomly enlarges the image. A value of 0.75 means that the image is enlarged to 75%, while 1.0 is a normal image size.

Fig. 6 shows the real time augmentation results that are generated after running the CNN model training.

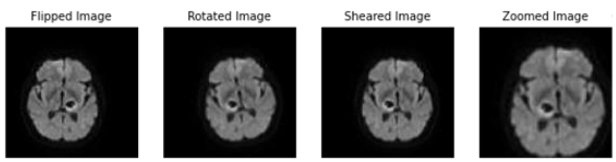


Fig. 6. DW-MRI image augmentation results.

D. K-Fold cross-validation

Evaluating machine learning models is very difficult. Usually, to divide the dataset into training and test sets it is necessary to use a training set to train the model and a test set to test the model. The next step is to evaluate the performance of the model based on the error matrix to determine the accuracy of the model. However, this method is not very reliable because the accuracy obtained for one test set can be very different from the accuracy obtained for different test sets. K-fold Cross-validation (CV) provides a solution to this problem by dividing the data into folds and ensuring that each fold is used as a test set at multiple CV points [16] [17].

This study uses 3,484 data. If using five-fold cross-validation, the data is divided into five folds of the same size where four folds will be used as training data and one fold is used as validation data. From a total of 3,484 ICH and normal image data, 2,787 data will be used at the training stage and 697 at the testing stage as test data. A total of 2,787 data used at the training stage will be divided into five (Each fold consists of 557 data), so that the amount of training data used is 2,230 data and validation data used is 557.

E. Performance Matrix for Classification

Three CNN models and machine learning algorithms were trained and evaluated by comparing four performance matrices such as: accuracy, precision, recall, and F1-score [16]:

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \quad (1)$$

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

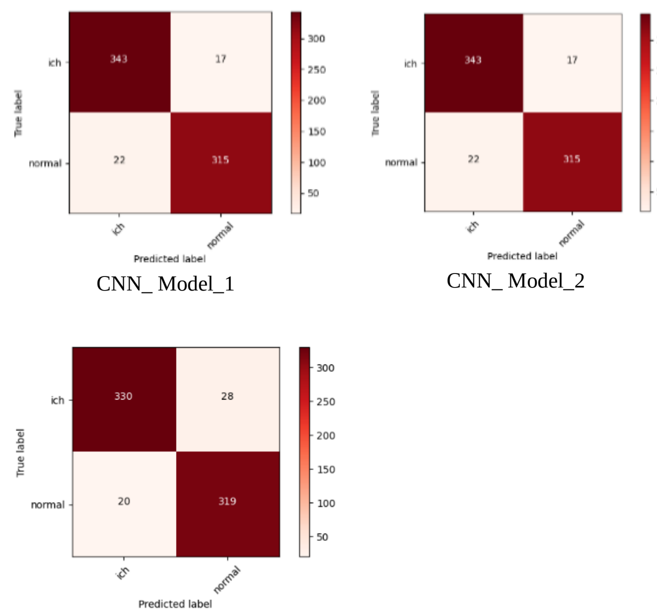
$$F\ Score = 2x\frac{Precision\ x\ Recall}{Precision+ Recall} \quad (4)$$

FN, FP, TN and TP are False Negative, False Positive, True Negative, and True Positive.

IV. Results and Analysis

A. CNN Model Performance Test

Comparisons are made by means of one parameter being a variable and the other parameters being assigned the same value for the three types of CNN architectures. Parameters compared were epoch, batch, and classification accuracy. Meanwhile, the other parameters are set to the same value, namely the number of filters is 32.64 and 128, with Stride 1 x 1, kernel 3 x 3, kernel pooling size 3 x 3, and using the SGD optimization function because it is stochastic. This means sampling random training data at each step, and then calculating gradients making it much faster because there is less data to manipulate at any one time. The image used as input from CNN is a rescaled grayscale image so that the size is 90 x 90 pixels.



CNN_ Model_1

CNN_ Model_2

CNN_ Model_3

Fig. 7. Confusion matrix for classification of Intracerebral Hemorrhage (ICH) stroke and normal brain images using 3 modified CNN models.

Based on the results of the tests that have been carried out, a confusion matrix for Intracerebral Hemorrhage (ICH) and normal brain images can be made using three modified CNN models as presented in Fig. 7. The test results show that the confusion matrix classification of the CNN_1 model and the CNN_2 model with 343 ICH image values is correctly predicted and 17 ICH images were not correctly predicted. Likewise, 315 normal images were correctly predicted as normal images and two normal images were predicted incorrectly as normal images. On the other hand, model_3 shows that 330 ICH images are correctly predicted as ICH images and 28 ICH images are predicted incorrectly as ICH images. Meanwhile, there are 319 normal images that can be predicted as ICH images, and only 20 ICH images that are predicted as ICH images.

Based on the performance results of the three CNN models shown in Table II, it can be seen that the accuracy values for

CNN model_1 and CNN model_2 have better performance than CNN_3. This is because the more convolution layers are generated, the more map features will also be. Therefore, the system experiences overfitting in classifying the image dataset.

TABLE II. CNN PERFORMANCE ANALYSIS

CNN MODELS	Precision (%)	Recall (%)	Specificity (%)	F1_score (%)	Acc (%)
CNN1	95%	93%	95%	94%	94.40 %
CNN2	95%	93%	95%	94%	94.40 %
CNN3	92%	94%	92%	93%	94.11 %

The algorithm used to test the validity of the accuracy results is k = 3, 5, 7 and 10 Cross-validation. The dataset is divided according to the number of k-folds into five folds in which there are 1,720 datasets, and at each iteration one fold is taken as a testing dataset and the other is used as a training dataset. The selection of the dataset for testing is adjusted according to the iteration order and the fold order, namely the 1st iteration folds 1, the 2nd iteration folds 2, and so on. After each training is finished, testing is immediately carried out to find the predicted value, and then the level of accuracy is calculated on average. The test results are shown in Table III.

TABLE III. EFFECT OF CROSS-VALIDATION

CNN Models	Precision (%)	Recall (%)	Specificity (%)	F1_score (%)	Acc (%)
CV (n=3)					
CNN1	66%	79%	59%	72%	68.95%
CNN2	70%	93%	61%	80%	76.81%
CNN3	58%	61%	56%	60%	58.48%
CV (n=5)					
CNN1	86%	84%	86%	85%	85.20%
CNN2	89%	85%	89%	87%	87.00%
CNN3	72%	86%	67%	87%	76%
CV (n=7)					
CNN1	93%	76%	94%	83%	84.84%
CNN2	86%	91%	85%	89%	88.09%
CNN3	73%	90%	66%	80%	77.98%
CV (n=10)					
CNN1	86%	84%	86%	85%	84.84%
CNN2	86%	87%	85%	87%	86.28%
CNN3	70%	76%	68%	73%	71.74%

Table III shows that for each k-fold tested, the CNN2 model has the best performance value compared to the CNN1 and CNN3 models.

B. Effect of Batch Size

In this test, the epoch value is set at 30 with SGD optimization and a dropout value of 0.5. Usually, large batch sizes are used because they allow computational acceleration. If you use a small batch size, it will take a very long time. However, there is a price to pay behind the speed of computing. Batch sizes that are too large will produce less than optimal results. The larger the batch size, the less accurate the results will be [18].

The test results are shown in Table IV, V, and VI. It can be seen that batch size 8 has the best performance with the highest accuracy of the several variations in batch size values for the three models tested. The larger the batch size value, the lower the accuracy value of each CNN model.

TABLE IV. EFFECT OF BATCH SIZE MODEL CNN_1

Number of Batch Size	Precision (%)	Recall (%)	Specificity (%)	F1_score (%)	Acc (%)
8	100%	100%	100%	100%	100.00 %
16	99%	96%	99%	98%	97.70%
32	94%	72%	95%	81%	83.00%
64	72%	78%	73%	75%	75.40%
128	69%	80%	64%	75%	72.02%
256	51%	56%	40%	54%	48.78%

TABLE V. EFFECT OF THE BATCH SIZE MODEL CNN_2

Number of Batch Size	Precision (%)	Recall (%)	Specificity (%)	F1_score (%)	Acc (%)
8	100%	100%	100%	100%	99.86%
16	99%	97%	99%	98%	98.13%
32	72%	95%	61%	82%	78.48%
64	75%	85%	74%	77%	77.04%
128	69%	88%	60%	77%	74.03%
256	50%	63%	35%	56%	49.21%

TABLE VI. EFFECT OF BATCH SIZE MODEL CNN_3

Number of Batch Size	Precision (%)	Recall (%)	Specificity (%)	F1_score (%)	Acc (%)
8	100%	98%	100%	99%	98.71%
16	100%	60%	100%	75%	80.06%
32	79%	53%	85%	64%	68.58%
64	71%	68%	72%	70%	70.16%
128	58%	99%	17%	73%	60.98%
256	51%	99%	5%	68%	52.65%

C. Effect of Number of Epoch

The next design trial was carried out with a batch size of 32 with SGD optimization and a dropout value of 0.5, and the number of epochs varied. The test results are shown in Table VII. The greater the epoch, the higher the accuracy acquired, namely 99.86% accuracy at epoch 90, which is the greatest accuracy value in the ICH stroke dataset.

TABLE VII. DEGREE OF ACCURACY WHEN THE NUMBER OF EPOCHS VARIES

Number of Epochs	Precision (%)	Recall (%)	Specificity (%)	F1_score (%)	Acc (%)
30	73%	98%	63%	84%	80.77%
50	77%	100%	71%	87%	85.51%
70	99%	98%	99%	98%	98.13%
90	100%	100%	100%	100%	99.86%

D. Comparison with Other Classification Methods

The following trials were conducted to compare the performance of the CNN2 Model design (as the best proven CNN design) with other classification methods, namely, SVM, Random Forest, Extra Trees, K Neighbors. For k–NN, the DW-MRI image dataset was tested using the k parameter of 3.

Meanwhile, for the SVM method, the dataset was tested using a linear kernel. Tests were carried out to classify the DW-MRI image dataset in the ICH or normal stroke class. The input data for the k-NN and SVM classifiers are the grayscale intensity values of each image pixel in the dataset.

The dataset used with all machine learning models uses 1720 normal images and 1720 ICH images with a training data and testing data ratio of 70:30. From the test results presented in Table VIII, it was found that the four machine learning methods (SVM, Random Forest, kNN, and Extra Trees) had poor performance, with levels of accuracy, sensitivity, and specificity all below 90%.

The CNN 2 model method produces the highest performance. This shows that the CNN 2 method can be implemented to classify DW-MRI images of stroke Intracerebral Hemorrhage (ICH) and normal brain images with good performance.

TABLE VIII. PERFORMANCE COMPARISON OF THE CNN2–SVM–KNN–RANDOM FOREST–EXTRA TREES METHODS ON ICH STROKE CLASSIFICATION

Method	Precision (%)	Recall (%)	Specificity (%)	F1_score (%)	Acc (%)
CNN2	95%	93%	9500%	94%	94.40 %
SVM	70%	70%	6900%	70%	70%
Random Forest	62%	79%	2500%	56%	62%
Extra Tress	57%	77%	14%	47%	57%
K Neighbors (k=3)	36%	36%	41%	36%	36%

V. CONCLUSIONS

From the results of the tests and analyzes that have been carried out, it can be concluded that the CNN algorithm can be used properly in the classification of DW-MRI images to distinguish stroke ICH images from normal DW-MRI images. In the first trial related to the CNN model performance test, the highest accuracy value was 94.40% for CNN1 and CNN2 compared to CNN3 because the more layers, the lower the accuracy value. To produce further performance on the CNN1 and CNN2 models, it was tested using the cross-validation method, the highest accuracy value was generated in the CNN 2 model for several variations of the number of k folds. Each CNN model was tested by changing the number of batch sizes. From the test results, the smaller the number of batch sizes (8), the higher the accuracy value and the number of epochs, the higher the number of epochs (90) the higher the accuracy value of 99.86%.

This study compares the basic CNN model scenario with the addition of layers to the original CNN model to produce the highest accuracy value. The dataset used is 1720 images for each class. Furthermore, each model is cross-validated with a different k to produce performance in each model as well as changes to batch size and epoch and comparison with machine learning models such as SVM, Random Forest, Extra Trees, and kNN. The results showed that the smaller the number of batch sizes, the higher the accuracy value and the number of epochs, the higher the number of epochs, the higher the accuracy value of 99.86%. Then, four machine learning methods with accuracy, sensitivity, and specificity below 90% are all compared to CNN2. The proposed CNN modification works better than the four machine learning models in classifying stroke images.

In the future, this study will be developed in terms of using CNN to classify 3D images so that classification classes can be multiplied. An example is not only to find out DW-MRI images of brain hemorrhage (ICH) or normal DW-MRI images, but can also find out blockages in several locations in the brain vessels with DW-MRI images.

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