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Adagrad Optimizer with Compact Parameter Design for Endoscopy Image Classification

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***Abstract*— Research on CNN Model and Adagrad Optimizer is expected to help identify diseases in the medical world. Especially in the field of image classification in Gastrointestinal endoscopic procedures . The research is specifically for the process of classifying medical images of Diverticulosis, Neoplasm, Peritonitis and Ureters . Previously, there have been quite a lot of studies on CNN and its various optimizers. However, those who have studied the Adagrad optimizer are not too many, especially those discussing the use of minimum parameters. The use of minimum parameters is expected to be one of the contributions of researchers in the fields of computing and medicine. The research was conducted to determine the use of the best parameters and obtain the highest level of accuracy. The research was conducted using minimum epochs starting from epoch 1, epoch 5, and epoch 10. Then the combination process between epoch and the number of convolution layers between 1 and 5 was carried out, resulting in 15 combinations. The test was carried out using 4000 images with 1000 images in each class. From the results of the test, the highest accuracy value was obtained, namely 82.875%. Then the highest average accuracy value was 81.625%. The average CPU usage ranges from 30.42% to 32.69%. And the average computation time ranges from 24.22 seconds to 229.542 seconds. From the research conducted with the use of minimum parameters, short computation time and little resource usage can produce a model with an average accuracy level above 70%.**

***Index Terms*— Adagrad Optimizer; CNN; Endoscopy Image; Image Classification; Minimum Parameters**.

I. INTRODUCTION

The number of optimizers used in Convolutional Neural Networks is one proof of the development of science[1] . Many optimizers used in *Convolutional Neural Network* (CNN) models include Adadelta, Adagrad, Adam, RMSprop and SGD. Each type of optimizer exhibits different performance and efficiency depending on the characteristics of the data and the architectural model. Previous research has described the applicability and accuracy of various optimizers on specific datasets[2], [3], [4] . However, there is no one that focuses on discussing the Adagrad optimizer with minimum parameters. Research related to CNN models usually uses many hypter parameters to get the best results.

Adagrad (Adaptive Gradient Algorithm) offers the advantage of dynamically adjusting the learning rate for each parameter based on its gradient history, enabling faster convergence on sparse data and efficient handling of diverse feature magnitudes[5], [6]. Compared to Adam or RMSprop, Adagrad requires fewer hyperparameters and computational resources, which makes it suitable for applications that require efficiency in both computation and memory usage. Previous works have shown its potential for resource-limited systems[7], [8], [9].

Despite these advantages, limited research has explored the use of Adagrad with compact parameter design in medical imaging contexts. Most studies rely on heavy computational resources or complex optimizers, leading to inefficiency in deployment. This study aims to evaluate the performance of Adagrad with minimal parameters for classifying gastrointestinal endoscopy images, emphasizing computational efficiency, accuracy, and model simplicity.

The research conducted this time focused on one optimizer to obtain the highest accuracy results with the shortest computing time and the least resource usage. This study applies a strategy of using minimum parameters on the optimizer to achieve efficiency in the model training process. The use of minimum parameters in the optimizer is expected to reduce the workload of the hardware used. The use of CNN models in deep learning, especially in terms of classification, is expected to help identify diseases in the medical world. Health care in the field of *Gastrointestinal endoscopic procedures* is one of the topics in this study. Gastrointestinal endoscopic procedures are medical procedures that use a special tool called an endoscope to examine, diagnose, or treat problems in the digestive tract, including the esophagus, stomach, small intestine, and large intestine[10], [11]. An endoscope is a long, flexible, and thin tool equipped with a camera at the end[12]. This tool allows doctors to see the inside of the digestive tract directly without the need for major surgery.

The medical image classification process carried out in this study focuses on several medical conditions only, namely, *Diverticulosis, Neoplasm, Peritonitis, Ureters* . *Diverticulosis* is a condition in which there are small pockets or balloons in the intestinal wall, especially in the large intestine. These pockets can form due to excessive pressure in the intestine[13]. *Neoplasm* is the medical term for a tumor or abnormal tissue growth. These tumors can be benign (harmless) or malignant (cancerous)[14], [15]. So, neoplasms include all types of abnormal cell growth in the body. *Peritonitis* is an inflammation of the peritoneum, which is a thin layer that lines the inner wall of the abdomen and protects the organs in the abdomen[16], [17], [18]. This inflammation is usually caused by infection, which can occur because an organ in the abdomen ruptures, such as a perforated intestine. Peritonitis is a serious condition and requires immediate medical attention. *The ureter* is a tube that connects the kidney to the bladder[19], [20], [21], [22], [23], [24]. Its job is to carry urine produced by the kidney to the bladder, where it is stored before being excreted from the body.

The next process is the process of creating models using minimum parameters, the parameters used are in Epochs and Convolution Layers. The use of epochs starts from the smallest epoch, namely 1, 5 and the largest epoch, namely 10. The computation process is carried out with a combination of epochs and convolution layers, each computation is carried out and produces 1 model. Then the number of Convolution Layers in this study starts from 1 convolution layer to 5 convolution layers. Where there are 5 combinations of layers and 3 combinations of epochs.

The last process carried out is the evaluation of the algorithm performance. The algorithm performance evaluation process is carried out using the Confusion Matrix. The algorithm performance is carried out on each model produced, so that the Precision, Accuracy, Recall and F-1 Score values can be calculated from the resulting models. The algorithm performance evaluation is carried out to obtain the best minimum parameter combination results. With the best parameters, it is expected that the use of the optimizer Adagrad can be more optimal in the classification process.

II. THEORY

The literature study process was conducted to explore more deeply what previous researchers have done in the image classification process. Several studies that discuss the CNN model and its optimizer include. The literature study process was conducted to explore more deeply what previous researchers have done in the image classification process. Some studies that discuss CNN models and optimizers include the following.

The study that discusses the CNN literature study in the cat image classification process by comparing 16 studies from previous researchers[25]. This study focuses on comparing the results of using the CNN model on the same object, namely cats. There is also another study[26]regarding CNN which also discusses the breed classification process in cats. This study discusses CNN and RMSprop optimizer. Another study that discusses CNN was also conducted for the caterpillar pest detection process in Aquaponic plants[27]. This study focuses on the caterpillar identification process with the CNN model which produces an accuracy value of 89%.

From several studies that have been conducted, some focus on hypter parameters, and some focus on increasing model accuracy against datasets. However, there is no specific research on the use of minimum parameters. In previous studies, there was a lot of focus on default parameters and the use of optimizers that were generally not detailed. One study that discussed the optimizer used was RMSprop. While this study focuses on the Adagrad optimizer to find the best parameters with the fastest computer time and the least resource usage

Endoscopy is a medical procedure performed to examine parts of the human body, especially the upper digestive tract or small intestine. Endoscopy is performed using a tool that is inserted into the digestive tract to capture images of the small intestine.[28]. With endoscopy it is possible to examine the digestive tract without undergoing surgery[29], this is certainly easier to do compared to examinations that involve surgery.

The model used in the study is CNN using the scikit learn library and using the python programming language. Classification is done using the Adagrad optimizer to find out the best parameters that can be used for the classification process.

III. METHOD

There are several stages carried out in this research, including literature review, data preprocessing, creating CNN models and performance evaluation. The flow of the research process carried out is shown in Figure 1 below.

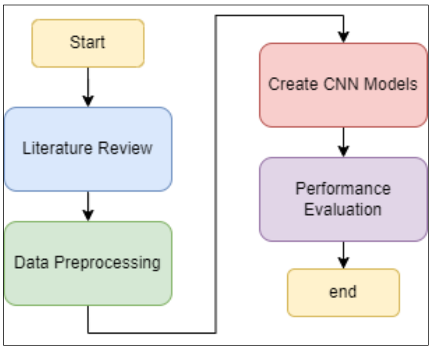

Figure 1. Flow of the research process carried out

A. Data Preprocessing

In preprocessing is done to ensure that the research can run smoothly. One of the important stages carried out is to prepare data in the research. Without processed data, research cannot be carried out. The data used in this study is a public dataset taken from kaggle. The dataset used is an image taken from the *Gastrointestinal endoscopic procedures process* , there are 4000 images in the dataset[30]

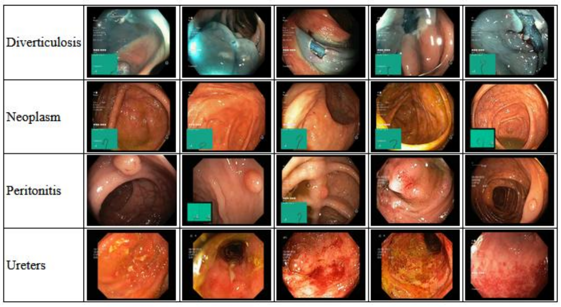

Figure 2. Gastrointestinal endoscopic dataset

The dataset consists of 4 classes with each class consisting of 1000 images. The classes in the dataset are Diverticulosis, Neoplasm, Peritonitis, Ureters. Each image used will later be divided into training data and testing data with a composition of 80% training data and 20% testing data. In detail, the flow of the data preprocessing process is seen in Figure 3 below.

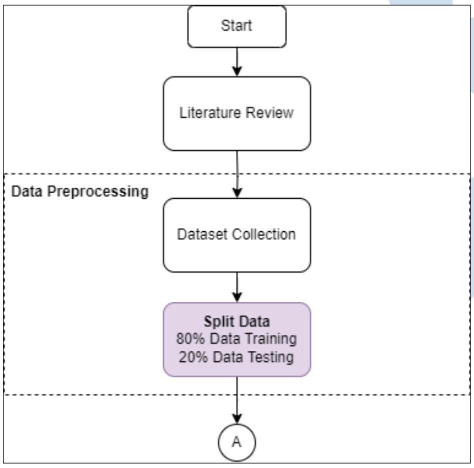

Figure 3. Initial research stage flow

From figure 3, it can be seen that 80% of the dataset used will be used as training data, which means the amount of training data used is 3200 images, and the testing data used is 800 images.

B. CNN Model

Convolutional Neural Networks (CNN) are models that are specialized for image recognition and have high accuracy in classifying objects in images[31], [32]. Convolutional Neural Networks (CNN) are a type of computer network that uses a mathematical technique called convolution. This technique allows the network to find patterns in data, such as images, by examining small parts of the data. In this way, even if certain patterns are not directly described in the data used to train it, the network can still recognize those patterns[33]. An illustration of the CNN model looks like the following figure 4:

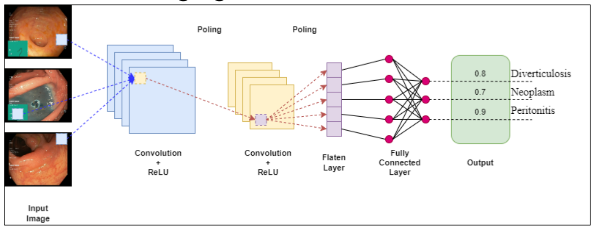

Figure 4. Illustration of CNN Model

The general equation regarding the convolutional layer operation looks like equation 1[29], [30] below.

$$S(i,j) = (I * K)(i,j) = \sum_{m} \sum_{n} I(i+m, j+n) \cdot K(m,n) \tag{1}$$

$K(m,n)$describes the convolution operation between an image I and a kernel Kat position (i,j). The process is carried out to calculate the value of each element in the convolution result S based on the interaction between the image and the kernel. In this formula, $S(i,j)$shows the convolution result at a point (i,j)calculated as the sum of the products of the elements that are interconnected between the image $I$and the kernel K. $I(i+m,j+n)$is the image element Iat position $(i+m,j+n)$, where mm and nn are indices that run along the kernel dimension K . The kernel $K(m,n)$is the element at position (m,n)in the kernel used to calculate the convolution.

In this study, CNN can be used as a solution for the visual data classification process in mapping neural network models using minimum parameters on epochs and the number of convolution layers. The use of dynamic optimization algorithms such as ADAGRAD can help adjust learning values continuously without the need to make adjustments at the beginning. The stages of the process carried out in creating a CNN model are shown in Figure 5 below.

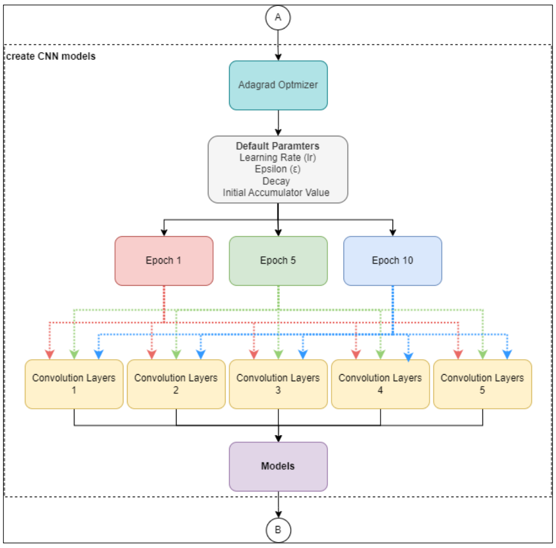

Figure 5. Flow of the CNN Model creation process with each parameter

The stages carried out in the process of creating CNN models start from selecting the use of optimizers (Adagrad Optimizer). The next stage is determining the parameter values of the optimizer used, namely learning rate (lr), Epsilon (ε), Decay, and Initial Accumulator value. The default parameters used at this stage contain the default values available in the pytorch library. The next stage is to determine the number of iterations (epochs) used starting from the minimum value available, namely 1, then 5 and 10. After the batch value is determined, it is continued by determining the number of convolution layers performed . The number of convolution layers used starts from 1 to 5 convolution layers.

1) *Adagrad Optimizer*

Adagrad (Adaptive Gradient Algorithm) optimizer is an algorithm used to improve the way computer models are trained, such as convolutional neural networks (CNNs). Adagrad's main advantage lies in its ability to automatically adjust the learning rate for each element of the model, according to how often the element is updated during training[36], [37], [38]. Using Adagrad, elements that are updated less frequently will experience faster learning improvements, while elements that are updated more frequently will experience slower learning[39].

This allows the model to adapt to different types of data and avoid learning too fast or too slow in some parts[40], [41]. Although Adagrad can speed up training on rare data, its drawback is that the learning rate decreases over time due to the accumulation of gradients from previous iterations, which can cause the model to stop learning earlier than desired. The equation used in the Adagrad optimizer looks like equation 2 below[42], [43].

$$\theta_{t+1,i} = \theta_{t,i} - \frac{\eta}{\sqrt{G_{t,ii} + \varepsilon}} \cdot g_{t,i} \qquad (2)$$

From equation 2, it is known that $\theta_{t+1,i}$ is the parameter result of the update from the adagrad optimizer. While $\theta_{t,i}$is the value of the previous parameter update result. η is the learning rate, ε is a small scalar parameter to avoid division by zero. The Adagrad optimizer works by calculating the gradient to adjust the learning rate, then changing the learning rate based on the calculated gradient. The Adagrad optimizer is designed to optimize the learning rate at each iteration, so it can improve the model accuracy without having to change the initial values.

2) *Adagrad Parameters*

Adagrad has several parameters used in the computational process in producing models. Commonly used parameters are Learning rate (lr), Epsilon (ε), Decay, and Initial Accumulator value. The learning rate (lr) parameter has a value of 0.01 which is the default value. Then Epsilon (ε) has a value of 1e-8 or 0.00000001, and decay has a value of 0.0, and the Initial Accumulator value has a value of 0.0[44]. The parameters that will be optimized in this study are Epoch and the number of convolution layers. The use of the epoch parameter starts from the smallest parameter, namely epoch 1, then epoch 5 then epoch 10. Then the number of convolution layers used in this study starts from 1 convolution layer, up to 5 convolution layers. With a total combination of epoch and convolution layer as many as 15 combinations.

C. *Performance Evaluation*

To measure the performance of the adagrad optimizer, an analysis was carried out using the confusion matrix method. Measurement of algorithm performance is carried out to determine the Precision, accuracy, recall and F1-Score values from the research that has been done. By using the confusion matrix, it is expected to know the performance of each model produced in the form of numbers. And the best classification model with the highest accuracy value and the shortest computing time, as well as the least resource usage, will be known. The flow carried out in the evaluation process is seen as in Figure 6 below.

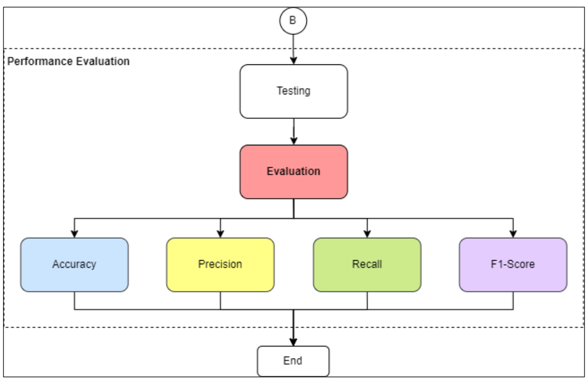

Figure 6. Performance evaluation process flow with confusion matrix

(2)

From figure 6, it can be seen that there are 4 measurement components that will be calculated in the evaluation process, namely accuracy, precision, recall and F1-Score. To be able to calculate these values, the TP, TN, FP and FN values must first be determined. The confusion matrix is arranged in the form of a table containing actual values and predicted values[45]as shown in table 1 below.

TABLE 1. CONFUSION MATRIX

	Positive Prediction (P)	**Negative Prediction (N)**
Positive Actual (P)	True Positive (TP)	False Negative (FN)
Negative Actual (N)	False Positive (FP)	True Negative (TN)

True Positive (TP) is the number of images that actually belong to a certain class and are correctly predicted by the model. False Positive (FP) is the number of images that are predicted to belong to a certain class, but actually belong to another class. False Negative (FN) is the number of images that actually belong to a certain class, but are predicted to be of another class. True Negative (TN) is an image that actually does not belong to a certain class and is correctly predicted[46], [47], [48].

Precision measures how many positive predictions are actually positive. In image classification, it indicates how many images are correctly predicted and are true. The *precision equation* looks like equation 3[49]below.

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

Recall (Sensitivity) is used to measure how many truly positive images the model successfully predicted correctly. This is also known as *True Positive Rate* (TPR). The *recall equation* looks like the following equation 4.

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

F1-Score Is the harmonic mean of precision and recall. *F1-Score* provides a better overview when we need a balance between the two. The *F1-Score equation* looks like the following equation 5.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (5)$$

IV. RESULT AND DISCUSSIONS

The test was conducted using 800 images as testing data with 200 images for each class . The testing process displays the predicted image and the actual image, as shown in Figure 7 below.

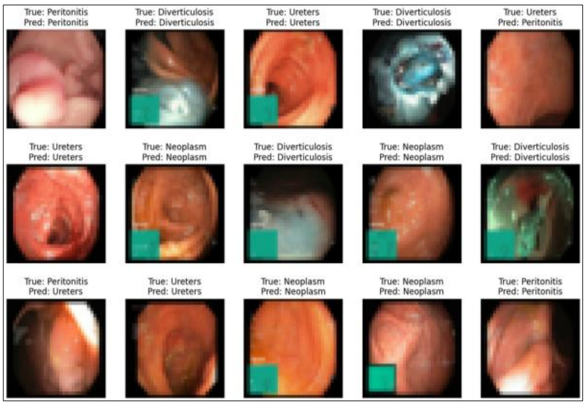

Figure 7. Endoscopic image classification process

Figure 7 shows the endoscopic image classification process by displaying the actual (true) values and predicted values from the Adagrad optimizer.

A. Adagrad Optimizer with Epoch 1

The process starts from the minimum epoch value of 1 combined with the number of convolution layers with a value of 1 to 5 convolution layers. The test results are shown in Table 2 below.

TABLE 2. TEST RESULTS OF EPOCH 1

Epoch	Number of Convolution Layers	Support	Precision	Recall	F1-score	Accuracy	Time (seconds)	CPU Usage (%)
1	1	800	0.77	0.76	0.77	76,375	24.09	31.5
1	2	800	0.79	0.78	0.78	77.5	23.46	31.75
1	3	800	0.74	0.69	0.67	68,875	23.97	32.15
1	4	800	0.69	0.69	0.67	69	24.25	32.1
1	5	800	0.69	0.69	0.69	69.125	25.33	32.45

From table 2, it can be seen that the highest accuracy value is 77.5 with 2 convolution layers. The fastest computing time is 23.46 seconds and the lowest CPU usage is 31.5%.

B. Adagrad Optimizer with Epoch 5

The second process is testing with an epoch value of 5 then combined with the number of convolution layers with a value of 1 to a convolution layer of 5. The test results are shown in Table 3 below.

TABLE 3. TEST RESULTS OF EPOCH 5

Epoch	Number of Convolution	Support	Precision	Recall	F1-score	Accuracy	Time (seconds)	CPU Usage (%)

	Layers							
5	1	800	0.84	0.83	0.83	82,875	113.21	31.85
5	2	800	0.81	0.81	0.8	80.5	123.73	31.1
5	3	800	0.83	0.83	0.82	82,625	158.03	23.35
5	4	800	0.71	0.71	0.66	70,625	110.17	33.2
5	5	800	0.78	0.76	0.75	76,375	116.33	32.6

From table 3, the highest accuracy value is 82,875 with 1 convolution layer. The fastest computing time is 110.17 seconds and the lowest CPU usage is 23.35%.

C. Adagrad Optimizer with Epoch 10

The final process is testing with an epoch value of 10 then combined with the number of convolution layers with a value of 1 to a convolution layer of 5. The test results are shown in Table 4 below.

TABLE 4. TEST RESULTS OF EPOCH 10

Epoch	Number of Convolution Layers	Support	Precision	Recall	F1-score	Accuracy	Time (seconds)	CPU Usage (%)
10	1	800	0.81	0.81	0.8	80.75	212.97	33
10	2	800	0.82	0.81	0.8	80,625	213.56	33.45
10	3	800	0.83	0.82	0.81	82.125	235.3	32.15
10	4	800	0.82	0.82	0.82	82.5	236.59	32.55
10	5	800	0.83	0.82	0.82	82.125	249.29	32.3

From table 4, the highest accuracy value is 82,625 with 2 convolution layers. The fastest computing time is 212.97 seconds and the lowest CPU usage is 32.15%.

D. Average Performance

Based on the epoch, the average performance value of the model generated from CNN and Adagrad optimizer is shown in Table 5 below.

TABLE 5. AVERAGE OF TEST RESULTS

Epoch	Support	Precision	Recall	F1-score	Accuracy	Time (seconds)	CPU Usage (%)
1	800	0.736	0.722	0.716	72.175	24.22	31.99
5	800	0.794	0.788	0.772	78.6	124,294	30.42
10	800	0.822	0.816	0.81	81,625	229,542	32.69

From table 5, it can be seen that the highest average accuracy value is 81.625 with the number of epochs 10. Meanwhile, the fastest average computing time is 24.22 seconds and the lowest average CPU usage is 30.42%.

V. CONCLUSION

From the research conducted using the CNN model and Adagrad optimizer, it was concluded that the highest accuracy value was 82.875%. The average CPU usage ranged from 30.42% to 32.69%. And the average computing time ranged from 24.22 seconds to 229.542 seconds. The average accuracy value is still above 70%, this can be seen in table 5, where the lowest average accuracy value is 72.175%. From the tests carried out, it can be concluded that a model with an accuracy level above 70% can be produced with minimum parameters on the Adagrad optimizer and CNN model. These results show that applying minimum parameters to the optimizer not only maintains a good level of accuracy, but also significantly speeds up the computation time, with the fastest average time being 24.22 seconds.

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