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Thai digit handwriting image classification with convolutional neural networks

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ABSTRACT

This paper aims to determine the efficiency in classifying and recognizing Thai digit handwritten using convolutional neural networks (CNN). We created a new dataset called the Thai digit dataset. The performance test was divided into two parts: the first part determines the exact number of epochs, and the second part examines the occurrence of overfits in the model with Keras library's EarlyStoping() function, processed through cloud computing with Google Colaboratory, and used a Python programming language. The main parameters for the model were a dropout of 0.75, mini-batch size of 128, the learning rate of 0.0001, and using an Adam optimizer. This study found the model's predictive accuracy was 96.88 and the loss was 0.1075. The results showed that using CNN in image classification and recognition. It has a high level of prediction efficiency. However, the parameters in the model must be adjusted accordingly.

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1. INTRODUCTION

In the information age, there is a lot of information that exists in the digital world and it was created by human hands and then imported into the computer such as handwritten text images, human handwritten text. When imported to a computer it can make machines distinguish who's handwriting. Handwriting is a movement directed from the brain, possibly unknowingly occurring at the time of writing [1]. Recognition of human handwriting it is increasingly important in the digital age because it is used in activities such as banking, mail sorting tasks. In the past, it was believed that machines could not process complex tasks. But at present, machines can process complex tasks more easily and with high accuracy [2]. In recent times, different systems have been developed or classified. It is intended to be used in various fields that require high efficiency in classifying or memorizing [3]. Research on human writing or handwriting recognition is challenging because each person has different writing styles, even in the same letter [4]. The human brain allows humans to interpret any different handwritten letters and numbers through the neural network within the brain. This allows us to learn complex new things. There is a wide variety of research that applies the neural network to simulate the human brain for reading handwriting in easier ways [5]. Handwriting recognition is an issue that is still being studied. Handwriting is easy to remember because there are many different things, such as different font styles and the writing styles of each person. Handwriting identity identification is very useful. Examples of applying to banking applications, such as handwriting recognition to confirm receipt of money or when paying [6]. A systemcapable of recognizing and classifying handwritten objects helps prevent complex problems [5]. This has resulted in the development of applications and algorithms that can better examine and analyze the semantics of handwritten images [3]. There are many algorithms used for searching, comparing, classifying, and recognizing image data. A popular algorithm for image classification is the machine learning algorithm and deep learning [7]. Deep learning is a subset of machine learning. The architecture of deep learning has several layers stacked inside and nonlinear processing deep learning can make decisions about new information by learning from a given dataset, through the neural network. Deep learning is efficient in processing large image data with high accuracy, so it is often used for image classification, image and video processing, speech recognition, text prediction, handwriting, and more [8]–[13]. One of the popular deep learning techniques for categorizing images is convolutional neural networks.

In this paper, the purpose of developing a model for classifying Thai digit handwritten using convolutional neural networks. Thai digits were invented for use during the reign of King Ramkhamhaeng the Great. Which has been 738 years. The origin of Thai digits comes from the Devanagari script of India, as well as Arabic digtis. It is currently used in Thailand's government offices. Examples of Arabic digits versus Thai digits as shown in Figure 1.

Arabic digit	0	1	2	3	4	5	6	7	8	9
Thai digit	๐	๑	๒	๓	๔	๕	๖	๗	๘	๙

Figure 1. Arabic digits vs Thai digits

2. RESEARCH METHOD

2.1. Convolutional neural network (CNN)

CNN is one of the most popular deep learning methods used for recognizing and classifying images and belongs to the supervised learning category [14], [15]. CNN is a feed forward neural network inspired by biology [16], [17]. A CNN consists of neurons or filters with weights and biases that are used to train the model to extract image properties. A CNN consists of two parts; feature extraction and classification [18]. The basic architecture of CNN is shown in Figure 2. It consists of the input layer, convolution layer, pooling layer, and fully connected layer. In the convolution layer and pooling layer, there can be more than one and send the data to the fully connected layer [14], [19].

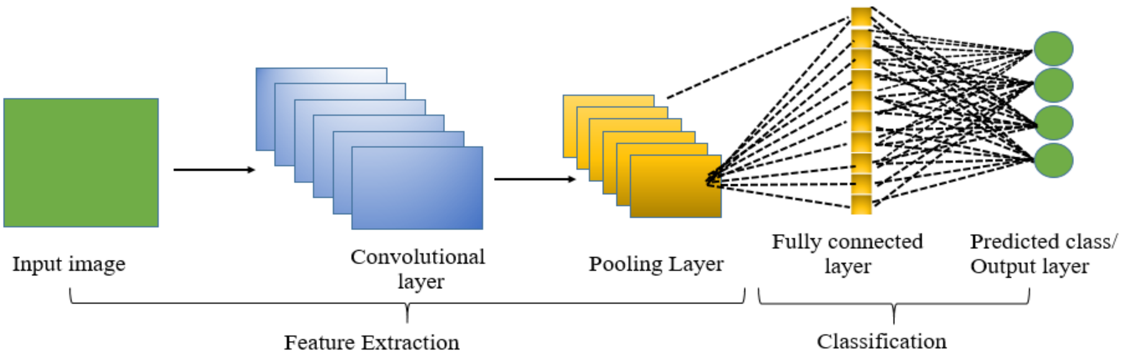


Figure 2. The basic architecture of convolutional neural network [13]

An example of a convolutional is shown in Figure 3. Let's start by multiplying the input with a feature detector or filter or a kernel that’s smaller than the input let's multiply element-wise. When you're done multiplying, move the kernel all the way to the right [12]. Then add all the results together and get the result in the feature map field. Then repeat all input data. You must specify the sliding windows to extract the feature.

An example of max pooling is shown in Figure 4. The max pooling process reduces the number of output parameters that the network must learn [20]. The size of the filter must be determined and then find the maximum value in the area where the filter is defined.

From Figure 3 convolutional operation, there’s a 4x4 input image and a feature detector 3x3. The first 3x3 input metric is multiplied element-wise by the feature detector. Then add the results for each value and put it in the first box of the feature map. In the figure, it's equal to 2. From Figure 4 is to find the Max Pooling, set the pooling size equal to 2x2, and put the largest value in the pooled feature map.

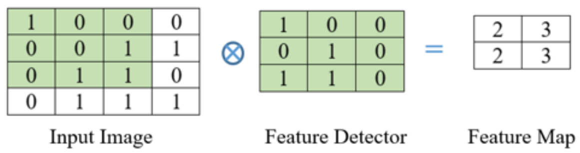


Figure 3. Convolutinal operation

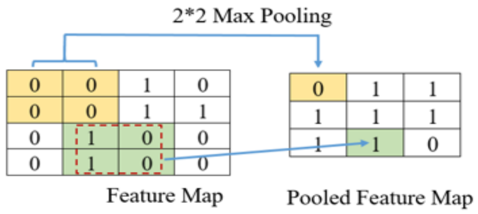


Figure 4. Max pooling

2.2. Model evaluation

In the model evaluation phase, the confusion matrix was used to verify the accuracy of the prediction and other minor discrepancies. Confusion matrix is used to show the performance of a trained model. The values obtained from the confusion matrix are accuracy, precision, recall, and F1-score. The confusion matrix is a table that describes the ability to predict actual vs. machine learning predictions. It describes the number of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN), it has the following meanings: TP is what the program predicts is "true" and is "true", TN is what the program predicts is "not true" and has a value "not true", FP is what the program predicts is "true" but is "false", FN is what the program predicts is "not true" but is "true". The formula for calculating values, accuracy, precision, recall, and F1-score shown in the (1)-(4) [21], [22].

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

$$Precision = \frac{TP}{(TP+FP)} \tag{2}$$

$$Recall = \frac{TP}{(TP+FN)} \tag{3}$$

$$F1\ Score = \frac{2*(Recall*Precision)}{(Recall+Precision)} \tag{4}$$

2.3. Data preparation

In this operation, it started by collecting handwritten Thai digits from a sample of 200 people, comprising students, citizens, and personnel from the public and private sectors, and writing Thai digits on the given form as shown in Figure 5. After that, scan the image from the form as a pdf file and crop the image into a single digit as a 28x28 pixels, as shown in Figure 6. By randomly selecting from a total of 14,950 images, it's called the Thai digit dataset. By randomly selecting images from a sample of 14,950 images called the Thai digit dataset. The Thai digit dataset is divided into 10 classes, which are digits ๐-๙ (0-9); each class has 1495 images. After that, the data is divided into two parts: the training dataset of 1,046 images and the testing dataset of 449 images, which is equal to the ratio of 70:30.

Figure 5. Thai digit handwritten form

Figure 6. Example of thai digit dataset

2.4. Model creation

The CNN model is based on the Python programming language and the Keras library. Cloud computing with Google Colaboratory is a cloud service based on Jupyter Notebooks used for machine learning education and research. Runtime is configured for deep learning and access to powerful GPU for free [23]. The structure of the CNN model in this section, generated with the Keras context, is shown in Table 1.

Table 1. Summary of CNN model structure

Layer (type)	Output shape	Param #
Input	(None, 28, 28, 3)	1568
conv2d (Conv2D)	(None, 25, 25, 32)	1568
max_pooling2d (MaxPooling2D)	(None, 12, 12, 32)	0
dropout (Dropout)	(None, 12, 12, 32)	0
conv2d_1 (Conv2D)	(None, 9, 9, 64)	32832
max_pooling2d_1 (MaxPooling2D)	(None, 4, 4, 64)	0
flatten (Flatten)	(None, 1024)	0
dense (Dense)	(None, 1024)	1049600
dense_1 (Dense)	(None, 10)	10250

From Table 1, the structure of the model consists of an Input layer, two layers of convolutional (Conv2D) and pooling (MaxPooling2D) and a dropout in the middle. Dropout is a regularization technique for deep learning [24] and uses the activation function as rectified linear unit (ReLU). After that, multidimensional data is transformed into vectors with flatten layer and fully connected in dense layer, which is a hidden layer in a neural network. In the last dens layer, we use activation function as Softmax because our output is multi-class. It can be written as a schematic showing the structure of the model as shown in Figure 5.

In Figure 7 model structure Thai digit classification of CNN, input image (RGB color) size 28x28x3 to convolutional will get output shape or feature map size 25x25x32, and when doing the max pooling process, it'll get an output shape is 12x12x32 which is halved from the convolutional process. After this layer, a dropout was applied with a probability of 75%. After that, it goes through the convolutional and max pooling processes again. It'll get output to shape sizes 9x9x64 and 4x4x64, respectively, and convert multidimensional data to one dimension in a flatten layer. Finally, set a dense layer with 10 classes of output.

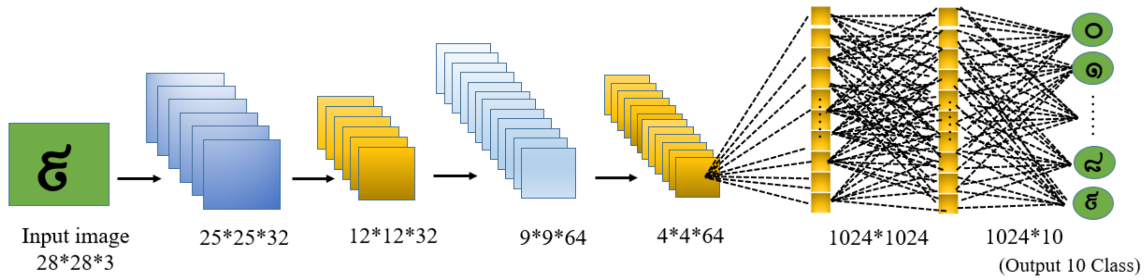


Figure 7. Model structure thai digit classification of CNN

2.5. Model training

Model Training is a process that teaches the machine to learn from the data prepared from the data preparation phase. The training of the model is divided into two parts to find the efficiency of the model. Considering the highest accuracy and the lowest loss, set the values for each part as follows:

a) Part 1 determines the exact number of epochs to train the model, without checking for overfitting in the model. The epoch values for the model training were 100, 200, 300, … , 1000 and the dropout equal 0.75; the mini-batch size equal 128; the learning rate equal 0.0001, and using an Adam optimizer, this is an algorithm for optimizing model training, resulting in reducing training and validation loss [25], [26]. The results for each epoch are shown in Figure 8.

b) Part 2 sets the maximum number of epochs equal to 1000 and monitors the model overfit, allowing the training process to stop before the maximum epoch value when the validation data loss value is greater than or equal to the previous loss minimum [27]. This technique keeps the model from overfitting by using callbacks from Keras EarlyStoping() function. Train the model three times. Each time it assigns a value to the patience variables of 10, 20, and 30, and other variables defined same as Part 1. The model training results are shown in Table 2 and Figure 9.

3. RESULTS AND DISCUSSION

The results of the model training with a Thai digit handwritten dataset using CNN, the objective is to find the best performance of the model. The results of the model training are divided into two parts.

a) Part 1 the results of the model performance evaluation. The accuracy and loss in the prediction of each epoch appear as shown in Figure 8.
From Figure 8(a) and (b), the model performance evaluation results. The predictive accuracy increased until the epoch was 400 with an accuracy equal to 96.93. After that, the accuracy began to drop significantly and it has a maximum accuracy of epoch 900, which has an accuracy equal to 96.97%. Considering the model's Loss, the Loss dropped to an epoch of 400. After that, there is an increasing trend. In conclusion, an epoch of 400 is best for training a model with a fixed number of epochs because it has high accuracy and low loss. If the epoch increases, the more time it takes to train the model.

b) Part 2 sets the maximum epoch equal to 1,000 and checks the model overfit with Keras library's EarlyStoping() function. The highest accuracy and the lowest loss, where patience is 30; accuracy is 96.88, and loss is 0.1075. It has fewer epochs compared to the patience of 20, which has more accuracy and loss. The results are shown in Table 2 and the accuracy and loss can compared as shown in Figure 9(a) and (b).
From the results of the experiment in Part 2, the predictive efficiency of the model was the best. When the patience parameter was set to 30, the time spent training and testing the model was 45 minutes, with the highest accuracy equal to 96.88 and the least loss equal to 0.1075. This is consistent with research by [21] using a convolutional neural network (CNN) to classify brain tumor images. Using magnetic resonance imaging (MRI), the model's efficacy was 96.1% accurate, and [28] research was conducted on gender classification using custom convolutional neural networks architecture. Provides a classification accuracy of not less than 96%, and [29]–[33] found that the accuracy was between 90%-98%.

The details of the confusion matrix are shown in Figure 10. Classification errors are caused by the similarity of the shapes and the characteristics of writing Thai Digit. The results of the evaluation of precision, recall, and F1-score for each class are shown in Table 3.

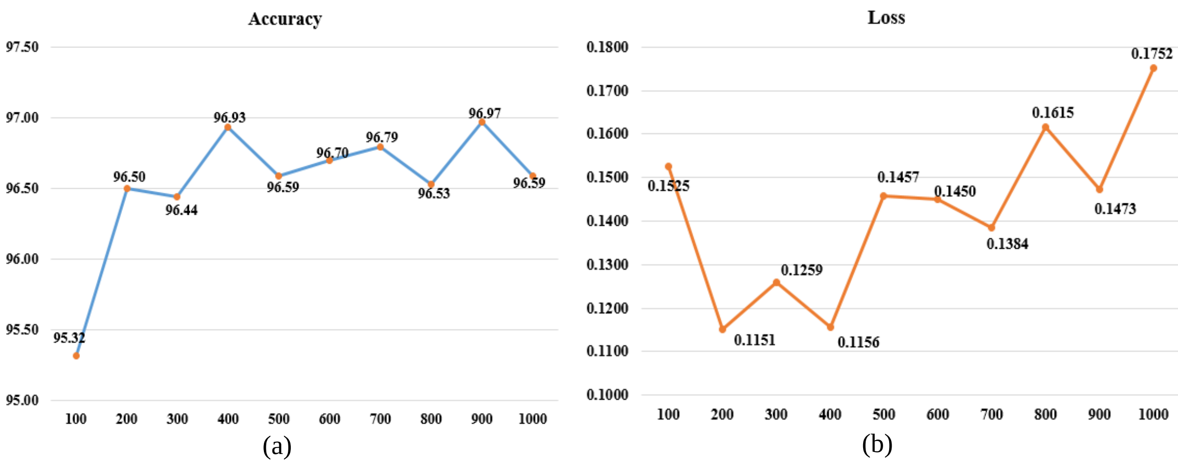
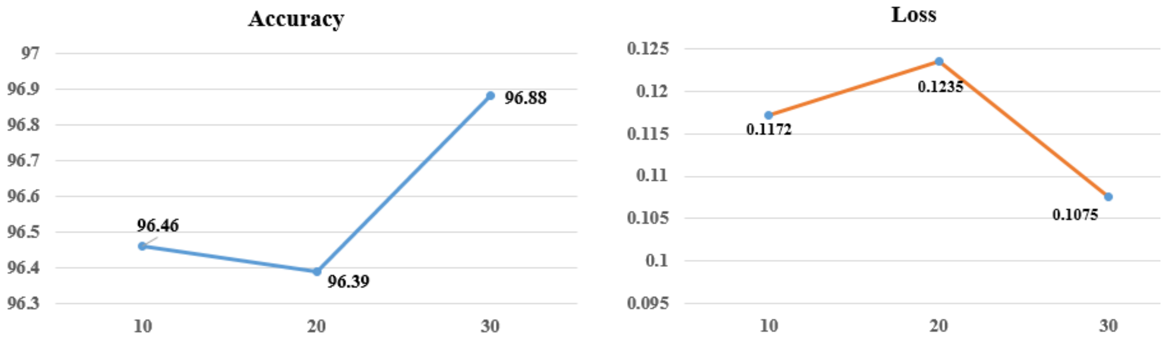


Figure 8. Result of model evaluation (a) accuracy and (b) loss

Table 2. Results of model training

Patience	Epoch	Time (min)	Accuracy	Loss
10	156	30	96.46	0.1172
20	224	49	96.39	0.1235
30	209	45	96.88	0.1075



(a) (b)

Figure 9. Performance of model with earlystoping function (a) accuracy and (b) loss

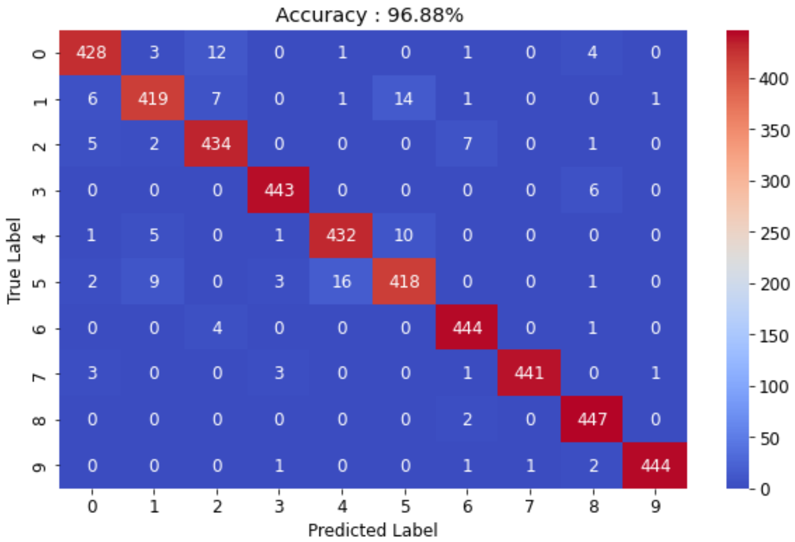


Figure 10. Best confusion metrix of model training

Table 3. Best Results of precision, recall, and F1-score

Class	Precision	Recall	F1-Score
๐ (0)	94%	98%	96%
๑ (1)	96%	93%	95%
๒ (2)	98%	93%	96%
๓ (3)	99%	100%	99%
๔ (4)	96%	95%	95%
๕ (5)	94%	94%	94%
๖ (6)	96%	99%	97%
๗ (7)	99%	97%	98%
๘ (8)	98%	99%	98%
๙ (9)	100%	99%	99%

4. CONCLUSION

We have created a new Thai digit dataset. Starting from creating a form for writing Thai digits, then crop into single digits and randomly select all 14,950 images, size 28x28 pixels, divided into 10 classes (0-9); each class has 1495 images. After that, the data were divided into 1046 training sets and 449 test sets, representing a ratio of 70:30. The process of training and testing the best performing model. We assign values to the following parameters: dropout equal 0.75, the mini-batch size equal 128, the learning rate equal 0.0001, using an Adam optimizer, and checking the model overfit with Keras library's EarlyStoping() function, and set patience parameter was set to 30. After setting the values, it shows an accuracy of 96.88 and a loss of 0.1075, which is the best. Therefore, it can be concluded that in creating a model to classify images of Thai digit handwritten with convolution neural network, the prediction accuracy is high and the loss is low, which is similar to other researchers. For future work, it is advisable to experiment with modifying additional parameters to suit the desired task in order to increase the predictive performance of the model to be more accurate.

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REFERENCES

[1] K. Chaudhari and A. Thakkar, "Survey on handwriting-based personality trait identification," *Expert Systems with Applications*, vol. 124, pp. 282–308, 2019, doi: 10.1016/j.eswa.2019.01.028.

[2] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," *Advances in neural information processing systems*, vol. 25, pp. 1097–1105, 2012.

[3] N. Sharma, V. Jain, and A. Mishra, "An analysis of convolutional neural networks for image classification," *Procedia computer science*, vol. 132, pp. 377–384, 2018, doi: 10.1016/j.procs.2018.05.198.

[4] U. Dwivedi, P. Rajput, M. K. Sharma, and G. Noida, "Cursive handwriting recognition system using feature extraction and artificial neural network," *Int. Res. J. Eng. Technol*, vol. 4, no. 03, pp. 2202–2206, 2017.

[5] S. Aqab and M. U. Tariq, "Handwriting recognition using artificial intelligence neural network and image processing," *International Journal of Advanced Computer Science and Applications*, vol. 11, no. 7, pp. 137–146, 2020, doi: 10.14569/IJACSA.2020.0110719.

[6] O. Sudana, I. W. Gunaya, and I. K. G. D. Putra, "Handwriting identification using deep convolutional neural network method," *TELKOMNIKA (Telecommunication, Computing, Electronics and Control)*, vol. 18, no. 4, pp. 1934–1941, 2020, doi: 10.12928/telkomnika.v18i4.14864.

[7] P. Wang, E. Fan, and P. Wang, "Comparative analysis of image classification algorithms based on traditional machine learning and deep learning," *Pattern Recognition Letters*, vol. 141, pp. 61–67, 2021, doi: 10.1016/j.patrec.2020.07.042.

[8] S. Giri and B. Joshi, "Transfer learning based image visualization using cnn," *International Journal of Artificial Intellegence and Application*, vol. 10, no. 4, pp. 47–55, 2019, doi: 10.5121/ijaia.2019.10404.

[9] S. T. Krishna and H. K. Kalluri, "Deep learning and transfer learning approaches for image classification," *International Journal of Recent Technology and Engineering (IJRTE)*, vol. 7, no. 5S4, pp. 427–432, 2019.

[10] B. Abhishek, K. Krishi, M. Meghana, M. Daaniyaal, and H. S. Anupama, "Hand gesture recognition using machine learning algorithms," *Computer Science and Information Technologies*, vol. 1, no. 3, pp. 116–120, 2020, doi: 10.11591/csit.v1i3.p116-120.

[11] A. I. Sapitri, S. Nurmaini, M. Sukemi, M. N. Rachmatullah, and A. Darmawahyuni, "Segmentation atrioventricular septal defect by using convolutional neural networks based on U-NET architecture," *IAES International Journal of Artificial Intelligence*, vol. 10, no. 3, p. 553, 2021, doi: 10.11591/ijai.v10.i3.pp553-562.

[12] E. C. Djamal, W. I. Furi, and F. Nugraha, "Detection of EEG signal post-stroke using FFT and convolutional neural network," in *2019 6th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI)*, 2019, pp. 18–23, doi: 10.23919/EECSI48112.2019.8977126.

[13] V. H. Phung and E. J. Rhee, "A deep learning approach for classification of cloud image patches on small datasets," *Journal of information and communication convergence engineering*, vol. 16, no. 3, pp. 173–178, 2018.

[14] H. Prasetyo and B. A. P. Akardihas, "Batik image retrieval using convolutional neural network," *TELKOMNIKA (Telecommunication, Computing, Electronics and Control)*, vol. 17, no. 6, pp. 3010–3018, 2019, doi: 10.12928/telkomnika.v17i6.12701.

[15] A. S. Permana, E. C. Djamal, F. Nugraha, and F. Kasyidi, "Hand movement identification using single-stream spatial convolutional neural networks," in *2020 7th International Conference on Electrical Engineering, Computer Sciences and Informatics (EECSI)*, 2020, pp. 172–176, doi: 10.23919/EECSI50503.2020.9251896.

[16] A. T. Radhi, W. H. Zayer, and A. M. Dakhil, "Classification and direction discrimination of faults in transmission lines using 1d convolutional neural networks," *Int. Journal of Power Electronics and Drive Systems*, vol. 12, no. 3, pp. 1928–1939, 2021, doi: 10.11591/ijpeds.v12.i3.pp1928-1939.

[17] S. Adnan, M. AI Achhab, B. E. Elmohajir, and A. Zbakh, "Neural network dealing with Arabic language," *International Journal of Informatics and Communication Technology (IJ-ICT)*, vol. 9, no. 2, pp. 73–82, 2020, doi: 10.11591/ijict.v9i2.pp73-82.

[18] M. Syarief and W. Setiawan, "Convolutional neural network for maize leaf disease image classification," *TELKOMNIKA (Telecommunication, Computing, Electronics and Control)*, vol. 18, no. 3, pp. 1376–1381, 2020, doi: 10.12928/telkomnika.v18i3.14840.

[19] P. Chandana, G. S. P. Ghantasala, J. R. V. Jeny, K. Sekaran, Y. Nam, and S. Kadry, "An effective identification of crop diseases using faster region based convolutional neural network and expert systems," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 10, no. 6, pp. 6531-6540, 2020, doi: 10.11591/ijece.v10i6.pp6531-6540.

[20] S. B. Jadhav, "Convolutional neural networks for leaf image-based plant disease classification," *IAES International Journal of Artificial Intelligence*, vol. 8, no. 4, pp. 328-341, 2019, doi: 10.11591/ijai.v8.i4.pp328-341.

[21] T. A. Sadoon and M. H. Ali, "Deep learning model for glioma, meningioma and pituitary classification," *International Journal of Advances in Applied Sciences (IJAAS)*, vol. 10, no. 1, pp. 88–98, 2021, doi: 10.11591/ijaas.v10.i1.pp88-98.

[22] B. Bhatkalkar, A. Joshi, S. Prabhu, and S. Bhandary, "Automated fundus image quality assessment and segmentation of optic disc using convolutional neural networks.," *International Journal of Electrical & Computer Engineering (2088-8708)*, vol. 10, no. 1, 2020, doi: 10.11591/ijece.v10i1.pp816-827.

[23] T. Carneiro, R. V. M. Da Nóbrega, T. Nepomuceno, G.-B. Bian, V. H. C. De Albuquerque, and P. P. R. Filho, "Performance analysis of google colaboratory as a tool for accelerating deep learning applications," *IEEE Access*, vol. 6, pp. 61677–61685, 2018, doi: 10.1109/ACCESS.2018.2874767.
[24] H. Wu and X. Gu, "Towards dropout training for convolutional neural networks," *Neural Networks*, vol. 71, pp. 1–10, 2015, doi: 10.1016/j.neunet.2015.07.007.
[25] K. Wróbel, M. Karwatowski, M. Wielgosz, M. Pietroń, and K. Wiatr, "Compressing sentiment analysis CNN models for efficient hardware processing," *Computer Science*, vol. 21, 2020, doi: 10.7494/csci.2020.21.1.3375.
[26] T. Dozat, "Incorporating nesterov momentum into adam," *ICLR 2016 workshop submission*, 2016.
[27] M. M. Badža and M. Č. Barjaktarović, "Classification of brain tumors from MRI images using a convolutional neural network," *Applied Sciences*, vol. 10, no. 6, p. 1999, 2020, doi: 10.3390/app10061999.
[28] F. H. K. Zaman, "Gender classification using custom convolutional neural networks architecture," *International Journal of Electrical & Computer Engineering (IJECE)*, vol. 10, no. 6, pp. 5758-5771, 2020, doi: 10.11591/ijece.v10i6.pp5758-5771.
[29] S. Z. M. Zaki, M. A. Zulkifley, M. M. Stofa, N. A. M. Kamari, and N. A. Mohamed, "Classification of tomato leaf diseases using MobileNet v2," *IAES International Journal of Artificial Intelligence (IJAI)*, vol. 9, no. 2, pp. 290-296, 2020, doi: 10.11591/ijai.v9.i2.pp290-296.
[30] R. Poojary, R. Raina, and A. K. Mondal, "Effect of data-augmentation on fine-tuned CNN model performance," *IAES International Journal of Artificial Intelligence*, vol. 10, no. 1, p. 84, 2021, doi: 10.11591/ijai.v10.i1.pp84-92.
[31] A. R. Luaibi, T. M. Salman, and A. H. Miry, "Detection of citrus leaf diseases using a deep learning technique," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 11, no. 2, pp. 1719-1727, 2021, doi: 10.11591/ijece.v11i2.pp1719-1727.
[32] I. B. K. Sudiatmika and F. Rahman, "Image forgery detection using error level analysis and deep learning," *TELKOMNIKA (Telecommunication, Computing, Electronics and Control)*, vol. 17, no. 2, pp. 653–659, 2019, doi: 10.12928/telkomnika.v17i2.8976.
[33] H. Kim, S. Lee, and H. Jung, "Human activity recognition by using convolutional neural network," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 9, no. 6, pp. 5270-5276, 2019, doi: 10.11591/ijece.v9i6.pp5270-5276.

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