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다중 블록 2D-컨볼루션 신경망을 이용한 효율적인 3D 프린터 출력 결함 분류 기법

Efficient 3D Printer Fault Classification Using a Multi-Block 2D-Convolutional Neural Network

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요 약

본 논문에서는 신속한 추론 시간과 낮은 계산 복잡도를 가지는 딥러닝(DL: deep learning) 모델을 사용하여 3D 프린터 출력 과정에서 발생하는 결함을 분류하는 새로운 방법을 제안한다. 제안하는 분류 기법은 3D 프린터 결함을 분류하기 위해 다중 블록 2D-컨볼루션 신경망(CNN: convolution neural network)을 사용하고 CNN 블록을 사용하여 fused deposition modeling(FDM) 3D 프린터에서 수집된 이미지 데이터 세트에서 특징을 추출한다. 제안된 모델은 MobileNet, AlexNet, VGG-11, VGG-16과 같은 기존 이미지 분류 알고리즘과 비교하여 성능을 평가하였다. 제안된 다중 블록 CNN은 기존 기법 대비 추론시간이 67.01% 빨라졌으며 87.56% 낮은 메모리 사용량과 최대 9.36%까지 감소시킨 매개변수를 사용함에도 높은 정확도를 보여준다. 이러한 성능은 제안된 3D 프린터 결함 분류 모델이 실시간 모니터링 조건에서 정확한 분류를 제공하는데 적합함을 보여준다.

Key Words : 3D Printing, CNN(convolutional neural network), Efficient model, Fault detection, Manufacturing

ABSTRACT

This paper proposes a novel fault classification method with an efficient deep learning (DL) model with fast inference time and lower computational complexity during the 3D printer printing process. Specifically, a multi-block 2D-convolutional neural network (CNN) is used to classify the 3D printer fault. In the proposed method, blocks of CNNs are used to extract the features from an image dataset that is gathered with a FDM 3D printer type. The performance evaluation of the proposed model is compared with existing image classification algorithms, such as MobileNet, AlexNet, VGG-11, and VGG-16. The results show that the proposed multi-block CNN classification model yields high accuracy with 67.01% faster inference time, 87.56% lower memory usage, and lower trainable parameters up to 93.36%. Furthermore, the proposed 3D model can provide an accurate classification in real-time monitoring conditions.

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Ⅰ. Introduction

3D printing technology has been rapidly expanding in many fields due to its advantages in fabricating different object structures with complex geometries and different materials [1]. The development of 3D printing technology requires intelligent approaches to produce efficient functions. However, the performance of the 3D printers is affected by the condition of their components. Among the different components of the 3D printer, the mechanical transmission is most prone to faults due to its severe working environment [2]. Faults in the mechanical transmission reduce the efficiency of the printing process, which also affects the quality of the printed product. Therefore, a 3D printing process fault classification must be developed to maintain the reliability of 3D printers.

Several researchers have utilized artificial intelligence (AI) in developing fault classification models. AI has always been an important factor which plays a substantial role in human workloads. As one of the subsets of AI, Deep Learning (DL) also plays a significant role in different fields and technologies such as automatic modulation enhancement [3], distributed-denial-of-services attack classification [4], and sensor data prediction [5]. Aside from those areas, DL also influences the manufacturing fields, especially in the 3D printer environment. DL is employed to maximize production efficiency and reduce waste material.

To improve the efficiency of 3D printers, DL is utilized in fault classification and task diagnosis. Recent studies of fault classification and diagnosis proposed various DL-based methods. In [6], a delta 3D printer fault diagnosis using a transfer support vector machine with attitude signals is proposed. In [7], a transmission line fault classification using hidden Markov models is proposed. In [8], an error possibility classification method is proposed. In the proposed method, an open circuit-based method is utilized to connect the 3D printer with an inverter.

Most of the current approaches focus on optimizing the efficiency of 3D printer manufacturing. In [9], a CNN-based approach is used to classify faults in photovoltaic arrays. Moreover, several fault detection and classification methods are proposed. In [10], a scheme for unified power flow controller compensated transmission lines connecting wind farms has been developed. In [11], a DL-based fault classification in the power distribution system using the Hilbert Huang transform and convolutional neural network is proposed. In previous studies, various DL methods were used for fault classification.

Fault classification with a numerical sensor dataset is used and compared in [12]. The result shows that DL with the numerical sensory data can extract the features better than other machine learning (ML) algorithms. In [13], temperature data prediction is demonstrated to avoid errors in the printing process with a DL method called temporal CNN. The authors claim that the proposed algorithm correctly detects the fault based on various sensory data. In [14], a 3D printer error detection considering the printed object's shapes is detailed. In the proposed method, a special-purpose box is used to capture a clear image and avoid light disruption. Then, the images are fed to the detection algorithm. Although the authors claimed that their proposed system is 100% effective, the number of shapes tested is limited to boxes.

Most of those mentioned studies utilize sensors data to detect the fault caused by 3D printers. Despite the prior fault classification approaches produced notable results, the classification performance is limited by the hardware. Specifically, the values obtained from the sensors affects the accuracy of the fault classification models. Thus, to provide a different point of view and increase the classification accuracy, this study evaluates the 3D printing process by using an image dataset.

Several popular image classification, such as MobileNet, AlexNet, VGG-11, and VGG-16 is pretrained with different dataset and formed with high cost DL model and complexity. Thus, to minimize the network cost and maintain the classification accuracy, an efficient CNN-based DL evaluated in this study. Therefore, the major contributions of this paper are listed as follows:

Propose a multi-block CNN-based DL model to classify the printing process with an image dataset.

Without sacrificing classification accuracy, an efficient DL model with low computational complexity based on memory usage and trainable parameters is proposed.

An image-based dataset that was captured with an FDM-based 3D printer in four different classes is provided.

The remainder of this paper is structured as follows. Section II mentioned the limitation of previous image classification methods. The proposed Multi-Block CNN-based model, hyperparameter selection and dataset preprocessing are explained in Section III. Sections IV and V provide detailed performance evaluations and conclude the paper, respectively.

Ⅱ. Problem Formulation

One technique to classify the printing process of the FDM 3D printer illustrated in Fig. 1. As for now, sensor is the most known approach to classify the fault in 3D printer. The quality of sensors affects the classification results. Hence, in this study we classify the fault based on image data captured from camera attached to the 3D printer to provide better classification results.

The existing image classification model mentioned in the previous section is widely used due to its capability to extract image features from large datasets. MobileNet is a mobile vision application that uses efficient CNN proposed by Google [15]. The MobileNet structure is formed on depthwise convolutions with average pooling, fully connected layers, and a softmax classifier. The existing MobileNet network provided by Keras is equipped with 2.26 million parameters. Another popular image classification network is AlexNet, which was proposed by Alex Krizhevsky et.al [16]. In total, 1.2 million high-resolution images from the LSVRC-2010 dataset with 1000 different classes are used to train this model. AlexNet is formed by 62.42 million parameters, which perform well across a wide range of datasets. In addition, VGG with various layer weight variations is also used to classify the high number of images [17]. VGG is formed with five blocks of convolution layers and a maxpool. VGG-11 and VGG-16 are the lowest and most popular VGG variations, with 101.51 and 107.01 million parameters respectively in 192 x 192 image data.

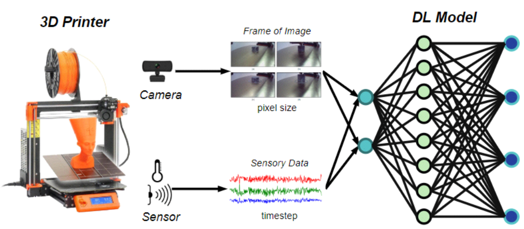

그림 1. 3D 프린터 결함 분류를 위한 2가지 방법
Fig. 1. Two approach of 3D printer fault classification.

Those mentioned image classification networks could be applied to the 3D printer environment to provide high classification accuracy. However, the fault detection time of the 3D printing process is highly affected due to the number of hyperparameters attached to those models. To overcome those limitations, an efficient DL model is needed to reduce the time required for the fault detection process without sacrificing accuracy.

Ⅲ. Proposed System

This section covers the proposed efficient CNN-based model to classify the faults in the 3D printing process. Moreover, the hyperparameter selection of the propsoed model, dataset description, and preprocessing are also discussed.

3.1 Proposed CNN-based DL Model

The proposed multi-block CNN-based model is used to identify the 3D printer's printing status with lower computational complexity and maintain the classification accuracy. The proposed architecture is illustrated in Fig. 2. First, an image frame as an input layer with a shape of 192 x 192 pixels is passed to the model. The proposed network is formed by three CNN blocks. Each block contains a Conv2D layer to extract the image feature with an

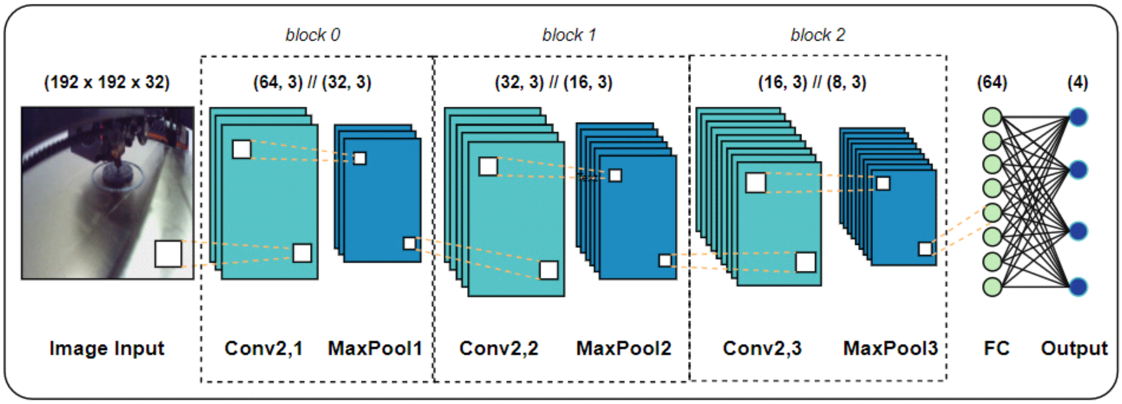

그림 2. 제안하는 다중 블록 2D-컨볼루션 레이어의 구성
Fig. 2. The architecture proposed Multi-Block 2D Convolutional neural network.

initial input shape. Also, a Max Pooling2D layer is added to extract the maximum value of convolution areas and provide better feature information after the convolutional layer. A different number of neurons unit are applied to each block to reduce the number of trainable parameters as well as minimize the memory usage of the model. In addition, a rectified linear unit (ReLU) is used as an activation function in all Conv2D layers and at the fully connected layer to normalize the feature extraction between 0 and 1, which is determined as follows:

$$f'(x) = \begin{cases} 0 & \mathrm{for}\,(x \le 0) \\ 1 & \mathrm{for}\,(x > 0) \end{cases} \quad (1).$$

Moreover, Adam as a network optimizer and mean square error (MSE) for loss function are utilized to compile the model. Finally, a fully connected layer with 64 neurons is added to the model, then an output layer is inserted at the end of the proposed network with four neurons with softmax activation function to classify the 3D printer's condition in the form of normalized values.

Compared with the existing deep learning models in image classification, the proposed model is built with a lower number of convolutional blocks. Despite the fact that the lower number of blocks produces lower accuracy, the proposed with an efficient layer design manages to maintain the performance results.

3.2 Hyperparameter Selection

The total number of neurons and layer combinations used in the proposed model are listed in Table 1. First, CNN-1 was equipped with higher neurons, and CNN-2 was initialized with minimum neruon units. The total number of neurons in each hidden layer of the proposed model is varied.

In the first block, a Conv2D layer is attached with 64 neurons and 16 neurons with 3 kernel sizes for CNN-1 and CNN-2, respectively. Then, with addition of another block, total number of neurons is reduced by half to maximize the learning process without increasing the model complexity. Finally, in the output layer, a total of 4 neurons are used, representing the total classes of the dataset that is captured. For the training hyperparameter, the Adam optimizer with a learning rate of 0.001 is used to

표 1. 다중 블록 2D-컨볼루션 신경망의 전체 레이어 정보
Table 1. Overall layers information of the proposed Multi-Block 2D Convolutional neural network.

Layer Name	Multi-Block CNN1	Multi-Block CNN2
Conv2D (0)	64, 3	16, 3
Max Pooling2D (0)	-	-
Conv2D (1)	32, 3	8, 3
Max Pooling2D (1)	-	-
Conv2D (2)	16, 3	4, 3
Max Pooling2D (2)	-	-
Fully Connected Layer	64	16
Output Layer	4	4

ensure the feature is well extracted. In addition, the network was trained with 25 epochs and 32 sizes of image batch.

3.3 Dataset Collection and Preprocessing

Recently, a limited number of datasets that exist are used to detect errors in the printing process of the 3D printer [18]. Limited dataset lead most of the researchers dive into sensor data fault classification. In this study, a dataset is first captured and labelled before being fed to the DL model. Fig. 3 depicts the overall mechanism for dataset collection with an FDM 3D printer.

The image dataset is captured in a time-lapse video mode with a 15-second duration for each printing process. Next, the time-lapse is used to extract around 50 images per video. In total, 2297 images containing four classes are collected. A sample of the obtained image dataset per class is shown in Fig. 4.

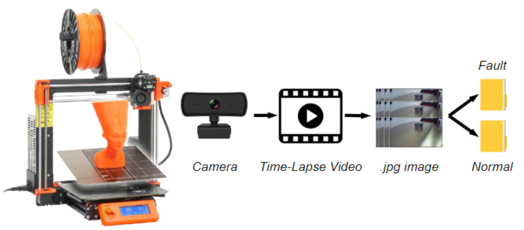

그림 3. FDM 3D 프린터를 이용한 이미지 데이터세트 수집
Fig. 3. Image dataset collection technique with FDM 3D printer

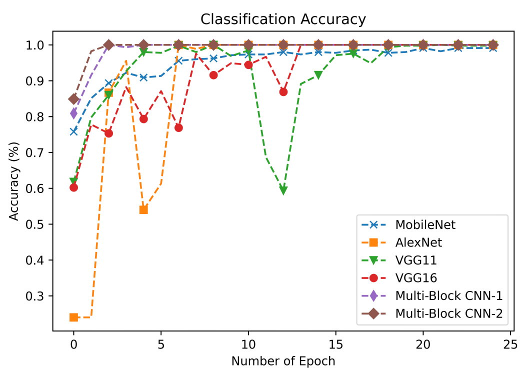

그림 4. 다양한 분류기법과 제안하는 다중 블록 2D-컨볼루션 신경망 분류기법의 분류 정확도 비교
Fig. 4. Classification accuracy of various image classification technique compared with the proposed multi-block CNN.

For the preprocessing, the dataset is divided into 80% training and 20% testing. All images are resized to 192 x 192 pixels with 32 batch sizes as multivariate data [19]. To produce optimal performance, autotune optimization from the TensorFlow library is used. Also, all the labelled image data is normalized with a minimum value of 0 and a maximum value of 255.

Ⅳ. Simulation Results

The simulation is run on top of a Jupyter Notebook powered by an Intel (R) Core (TM) i9-10940X CPU running at 3.30GHz. Various performance metrics were used to evaluate the proposed Multi-Block CNN model for 3D printer fault classification, such as: (1) classification accuracy, (2) total trainable parameters, (3) training time, (4) prediction time, (5) total memory usage, and (6) confusion matrix. To show the model performance as opposed to the existing image classification technique. The proposed model is compared with MobileNet, AlexNet, VGG-11, and VGG-16.

4.1 Classification Accuracy

In terms of classification accuracy, the proposed model achieved 100% accuracy with stable performance. The overall performance of all compared models is illustrated in Fig. 5. It can be seen that the proposed multi-block CNN is able to

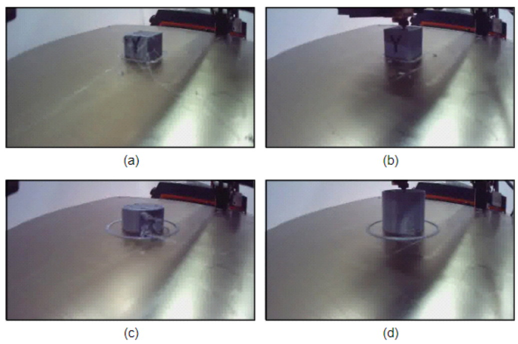

그림 5. 샘플 데이터세트 이미지: (a) 결함 큐브; (b) 일반 큐브; (c)결함 실린더; (d) 일반 실린더
Fig. 5. Sample of dataset images: (a) faulty cube; (b) normal cube; (c) faulty cylinder; (d) normal cylinder.

maintain the accuracy performance compared with other models. More than 15 and 20 epochs are required for AlexNet and MobileNet to generate maximum accuracy, respectively. Additionally, for VGG-11 and VGG-16 models, the classification accuracy is fluctuating. Therefore, the proposed multi-block 2D Convolutional neural network is better than the existing models based on accuracy and faster convergence time.

4.2 Model Complexity Comparison

Table 2 details the performance comparison among all the algorithms compared in this study based on accuracy, trainable parameters in millions, and single image prediction time in seconds. It can be seen that, based on the accuracy, all models successfully provide 100% classification accuracy. Despite the similar accuracy generated by all algorithms, a fast and efficient network is required to minimize waste material during the 3D printing process. As it is depicted in Table 2, the existing image classification technique is attached to a high number of trainable parameters, which affects the inference time. Inference or prediction time is calculated as the total time required to generate a single image classification result with new test data. VGG-16 is equipped with 101.51 million parameters and requires 16.85 ms to classify single image data. For other models, AlexNet and MobileNet are attached with 62.42 and 2.26 million trainable parameters and require 4.58 ms and 3.85 ms, respectively, to make a prediction. The limitation of the high number of parameters installed in DL models implies an increase in the prediction time. It is proven by the proposed multi-block CNN1 and CNN2 models with 0.61 and 0.15 million parameters, which can generate shorter prediction times of 2.07 ms and 1.27 ms, respectively.

표 2. 모든 알고리즘의 성능 비교
Table 2. The performance comparison among all compared algorithms.

Model	Accuracy (%)	Trainable Parameter (M)	Inference Time (ms)
MobileNet [15]	100	2.26	3.85
AlexNet [16]	100	62.42	4.58
VGG-11 [17]	100	101.51	9.01
VGG-16 [17]	100	107.01	16.85
MultiBlock-CNN1	**100**	**0.61**	**2.07**
MultiBlock-CNN2	**100**	**0.15**	**1.27**

In addition to the model complexity, an evaluation of memory usage in floating-point operations per second (FLOPS) and training time is performed. Fig. 6 illustrates the total FLOPS demanded by each model compared in this study. The proposed multi-block CNN2 achieves the lowest number of operations per second with a value of 0.056 G, followed by MobileNet, proposed multi-block CNN1, AlexNet, VGG-11, and VGG-12 with total FLOPS 0.45G, 0.495G, 1.879G, 11.194G, and 22.749G, respectively. Although MobileNet has a lower FLOPS value compared with the proposed multi-block CNN1, the performance of the proposed method is still better with faster inference time.

Fig. 7 depicts the training time required for all the compared algorithm in this study. The training time is calculated based on the time duration from the first epoch until the last epoch performed. It can be observed that the longest training time in 25 epochs was performed by the VGG-16 with 5843.24 s, followed by the VGG-11 , multi-block CNN1, AlexNet, MobileNet, and multi-block CNN2 with 2484.92 s, 684.33 s, 523.82 s, 222.95 s, and 217.74 s, respectively. The proposed model multi-block

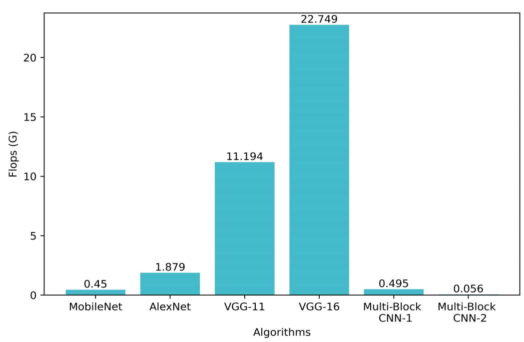

그림 6. GigaFlops에서의 전체 알고리즘 메모리 사용량
Fig. 6. Memory usage of all algorithms in GigaFlops .

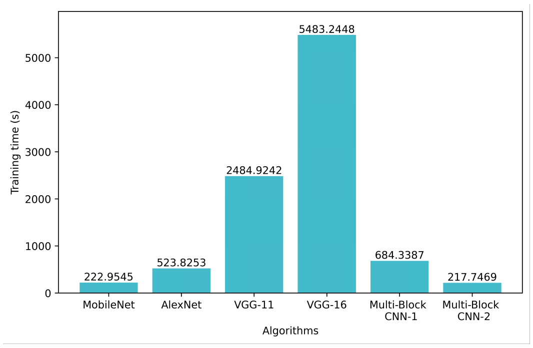

그림 7. 전체 알고리즘의 학습 시간
Fig. 7. Training time of all algorithms in seconds.

CNN2 successfully outperforms the other models with an efficient number of neurons that maintain the accuracy as detailed in Table 2.

4.3 Confusion Matrix

The confusion matrix that is obtained with test data in various algorithms for the fault classification is shown in Fig. 8. In total, 450 images of the 3D printer printing process were used as input for the prediction test. It can be seen that the overall algorithm produces good classification results with four different classes. However, the MobileNet network failed to determine the fault condition in the cylinder and cube images. This phenomenon occurs due to an insufficient layer attached to the model to extract feature information from the 3D printing image data. In the proposed model, three multi-block convolutional layers are applied to extract the feature data sequentially.

V. Conclusion

The reduction of waste material or products with poor quality during the 3D printing process is addressed in this paper. Sensor device limitations were considered in this paper to increase the classification accuracy. Image data is more suitable than sensory data as the algorithm can learn the model shape accurately. Thus, the dataset consists of a total of 2297 image files gathered in this study.

A novel multi-block CNN algorithm to classify the 3D printer condition is proposed. The

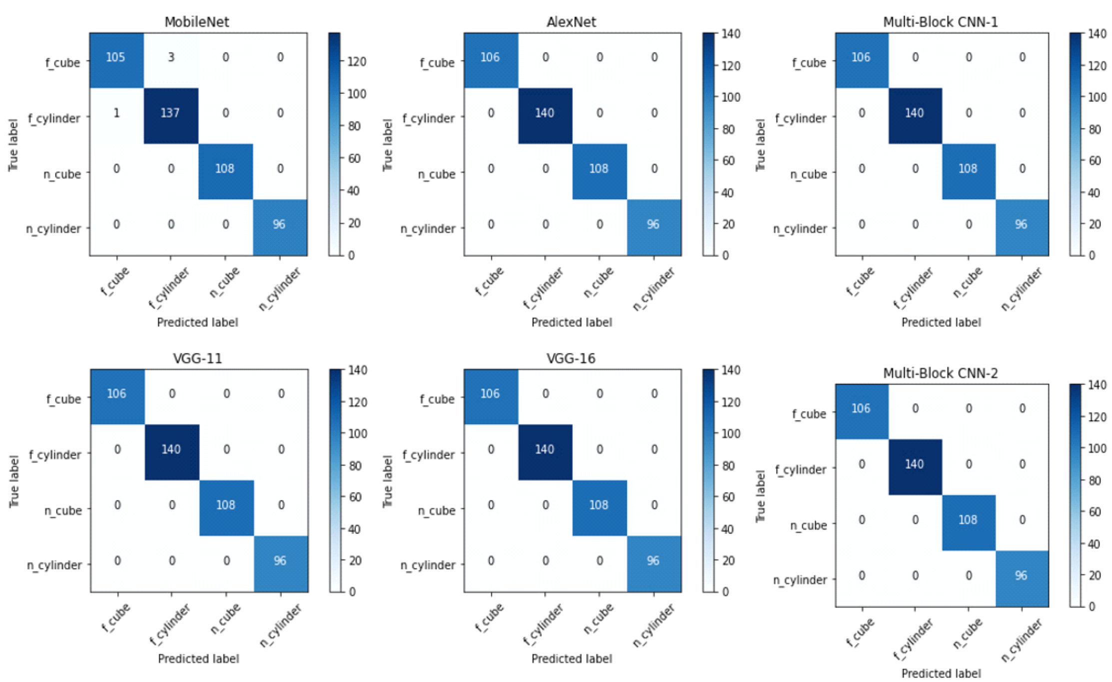

그림 8. 전체 이미지 분류 알고리즘과 제안하는 다중 블록 2D-컨볼루션 신경망의 Confusion 매트릭스 비교
Fig. 8. Confusion matrix of all image classification algorithms and the proposed multi-block CNN with 450 test data.

multi-block convolutional layer is installed with a limited number of neurons to reduce the memory usage and inference time without ignoring the classification accuracy. The comparison was conducted with the existing popular image classification, MobileNet, AlexNet, VGG-11 and VGG-16. Based on the results, the proposed multi-block CNN2 is better than the existing model with 93.36% lower trainable parameters, 87.56% lower memory usage, and 67.01% faster inference time with 100% classification accuracy. Hence, the proposed model is suitable in a real-time environment.

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